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Charles University

INCOME INEQUALITY AS LONG-TERM CONDITIONING FACTOR OF MONETARY TRANSMISSION TO BANK INTEREST RATES IN EA COUNTRIES

Tomas Domonkos

Boris Fisera

Maria Siranova

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$$\frac{1!}{(m-1)!} p^{m-1} (1-p)^{n-m} = p \sum_{\ell=0}^{n-1} \frac{\ell+1}{n} \frac{(n-1)!}{(n-1-\ell)! \ell!} p^{\ell} (1-p)^{n-1-\ell} = p \frac{n-1}{n} \sum_{\ell=0}^{n-1} \left[\frac{\ell}{n-1} + \frac{1}{n-1} \right] \frac{(n-1)!}{(n-1-\ell)! \ell!} p^{\ell} (1-p)^{n-1-\ell} = p^2 \frac{n-1}{n} +$$

Institute of Economic Studies,
Faculty of Social Sciences,
Charles University in Prague

[UK FSV – IES]

Opletalova 26
CZ-110 00, Prague
E-mail : ies@fsv.cuni.cz
<http://ies.fsv.cuni.cz>

Institut ekonomických studií
Fakulta sociálních věd
Univerzita Karlova v Praze

Opletalova 26
110 00 Praha 1

E-mail : ies@fsv.cuni.cz
<http://ies.fsv.cuni.cz>

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Income Inequality as Long-term Conditioning Factor of Monetary Transmission to Bank Interest Rates in EA Countries

Tomas Domonkos^{a,b}

Boris Fisera^{a,c}

Maria Siranova^a

^aSlovak Academy of Sciences, Slovakia

^bComenius University in Bratislava, Slovakia

^cInstitute of Economic Studies, Faculty of Social Sciences, Charles University,
Prague, Czech Republic, Email (corresponding author): boris.fisera@fsv.cuni.cz.

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Abstract:

In this paper we investigate the effect of income inequality on the transmission of standard and unconventional monetary policy shocks to bank loan rates. We hypothesize that income inequality might encapsulate important characteristics of credit market demand. We use an interacted panel error correction model to examine a set of EA countries over the years 2008-2016. Our findings suggest that higher income inequality hinders the transmission of standard monetary policy to consumer loans and limits the use of unconventional monetary policy in the housing loans segment. Conversely, more unequal societies are characterized by stronger monetary transmission in the small firm loans segment.

JEL: D31, E21, E52, E58

Keywords: interest-rate pass-through, interacted PMG, income inequality, standard monetary policy, unconventional monetary policy

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1. Introduction

In the presence of the current prolonged period of zero-lower bound constraint in the Euro Area, the possible distributional effects of unconventional monetary policy have raised serious concerns among many policymakers. The general consensus has so far produced the common belief that standard monetary policy is likely to lead to changes in overall income inequality (Coibion et al., 2017). On the other hand, the most recent empirical literature still provides only vague guidance as to whether the effects of unconventional monetary policies are transmitted to income inequality levels (Colciago et al., 2019). In any case, the overall redistributive effects of monetary policy are likely to be modest (Ampudia et al., 2018).

Empirical evidence shows that income inequality has remained relatively persistent over the short to medium term. Thus, while short-term monetary shocks might introduce small disturbances into income dispersion, long-term trends resulting in cross-country heterogeneity are likely to be driven by more fundamental factors (Tridico, 2012; Hasan et al., 2020; Furceri and Ostry, 2019). From this perspective, persistent income inequalities may not only affect overall aggregate savings (Bunting, 2009), economic growth (Berg et al., 2018), financial development (Hasan et al., 2020) or lead to a financial crisis (Kumhof et al., 2015) but they may also severely limit the conduct of any stabilizing economic policy, monetary policy notwithstanding.

Recently, it has been argued (Voinea et al., 2018) that persistent heterogeneity in income or wealth distribution might hinder the transmission of monetary policy impulses into the economy and, as a result, limit its conduct, especially during those times when it is most needed. One of the possible explanations presupposes that income distribution itself may reflect structural differences embodied in the financial systems and as such affect the demand side in credit markets (Krueger and Perri, 2006). Rajan's hypothesis (Rajan, 2010) ventures even further by postulating that monetary policy itself might unintentionally react to the deepening of income inequalities and engage in periods of excessive monetary easing.

To build upon this stream of literature, in this paper we investigate the link between the effects of persistent long-term income inequalities and the conduct of monetary policy.

Firstly, we assess the possible effects of income inequality on the transmission of monetary shocks to bank loan rates (i.e., intermediate targets). While, the literature provides some very limited empirical evidence on the effects of income inequalities on credit provisioning (Borowski et al., 2017), the transmission of monetary shocks to bank loan rates in the presence of sustained income inequalities has not yet been thoroughly studied. This is all the more intriguing since a well-functioning interest-rate pass-through (IRPT henceforth) represents the cornerstone of efficient conduct of any monetary policy.

Secondly, we replace the traditional measure of income inequality, the Gini index, with individual indicators measuring the share of the total population earning a certain proportion of income. We argue that this measure is a more suitable approach to capture heterogeneity in income distribution across countries and is more in line with recent advances in DSGE modelling (Areosa and Areosa, 2016). The models with heterogeneous agents incorporate the share of households characterized by uneven access to credit and labour markets rather than one measure of overall income distribution. Furthermore, as we study the role of inequality in affecting the transmission of monetary policy to bank loan rates, we also posit that credit constraints faced by particular segments of the population play an important role. As an additional contribution, by using micro-level data from the EU-SILC database, we are also able to derive the share of low-, middle- and high-income groups that maximises the effect of inequality on the transmission of monetary policy shock to intermediate targets.

Lastly, we separately investigate the effects of standard and unconventional monetary policy tools. The diverse impact of unconventional monetary policy measures in comparison to standard policies has been demonstrated in several publications (Horvath et al., 2018). As the majority of financial assets are owned by higher income households (de Bondt et al., 2020), the effects of quantitative easing policies, as the most extensive of the post-crisis unconventional monetary policies in the Euro Area (EA), may differ given the underlying distribution of financial wealth and associated income inequalities.

Understanding the limitations of interest rate transmission is important for the sustainability of the common monetary area, the euro area notwithstanding, all the more so when fiscal

redistribution among members is insufficient. Even in the presence of initially highly synchronized business cycles, monetary policy in responding to common adverse exogenous shocks, if transmitted unequally to individual member states, may ultimately result in asynchronous future growth trajectories. An over-sensitive response in one member state may substantially shorten the length of economic recovery, while a less than optimal extent of monetary easing may be conducive to prolonged periods of economic slack. Potential structural differences that weaken monetary policy thus make its conduct also less effective, predictable, and credible.

Using monthly data from 2008 to 2016 for a panel of 15 EA member states, we employ an interacted pooled mean group (PMG) estimator to estimate an ARDL model. This approach is widely used in the IRPT literature (Belke et al., 2013; Gambacorta et al., 2015). The conditioning effect of income inequality is introduced via an interaction term with the EONIA interbank rate serving as a proxy for conventional monetary policy, and three measures of unconventional monetary policy (Horvath et al., 2018). We first proxy income inequality with a share of the population earning particular percentiles of overall income, with the selected percentiles covering the entire income distribution. Based on the results attained from these individual regressions, we calculate an aggregate inequality ratio that relates the share of middle- and/or high-income earners to the bottom side of the income distribution and test for its significance in explaining heterogeneity in the IRPT across the member states of the Euro Area.

Our results suggest that income inequality plays a significant role in explaining cross-country heterogeneity in standard monetary transmission to consumer bank loans rates, as well as to housing loans rates in the case of unconventional monetary tools. Additionally, small firm loans rates tend to respond more sensitively to increasing income inequality irrespective of monetary policy. These findings for consumers loans segment may, therefore, be considered as supportive for the hypotheses put forward by Voinea et al. (2018) and Guerello (2018) who argue that higher inequality may hinder the effectiveness of monetary pass-through, in particular in the presence of zero-lower bound. On top of that, the presence of more than two distinct groups of the population is documented in several cases suggesting that using an overly simplistic split between financially constrained and financially included individuals (e.g. Areosa and Areosa (2016)) may be insufficient in both the empirical and

theoretical work. As the income inequality tends to show a rather persistent behaviour over short to medium term, existing structural differences among EA member states might also introduce new barriers towards future economic convergence.

The rest of the paper is organized as follows. Section 2 outlines the relevant literature, while section 3 outlines the empirical methodology and introduces our data. The results are reported in section 4 and section 5 concludes the paper.

2. Literature Review

The relationship between income inequality and monetary policy is a complex one, not only because the effective conduct of the latter is highly dependent on the underlying structure of the financial system, especially the credit market. Leroy and Lucotte (2015), Horvath et al. (2018) or Gregor et al. (2019) show that banking system features characterizing the supply side of credit markets fundamentally affect the transmission of shocks to monetary policy intermediate targets.

Nonetheless, most of the studies have so far only focused on causality stemming from monetary policy to inequality, rather than vice versa. This strand of literature has introduced several transmission channels through which monetary policy may (un-)intentionally affect wealth and income distribution (Ampudia et al., 2018). In general, the effects of monetary policy shocks differ depending on the choice of monetary measures, as well as the channels of transmission. Among the standard tools, the indirect channel affecting the income of households via improvements in the labour market conditions has been shown to play a prominent role (Ampudia et al., 2018). However, while standard monetary policy conducted via innovations to key policy rates affects inequality (Coibion et al., 2017), the final word on the effects of unconventional measures has not yet been spoken (Colciago et al., 2019).

On the other hand, the list of studies focusing on causality stemming from income inequalities to the credit market is rather limited, with the findings often being contradictory. Krueger and Perri (2006) develop a theoretical model, where the structure of the credit market is endogenous and may evolve responding to changes in income inequality. Tridico (2012) argues that the recent increase in permanent income inequality which resulted from a fall in workers' bargaining

power has also brought about an increase in demand for credit. Additionally, a few authors have pointed out that, in the long-run monetary policy has a tendency to react to persistent income inequalities by excessive monetary easing. Fitoussi and Saraceno (2010) and Rajan (2010) express the opinion that depressed aggregate demand, which reflected a deepening of income inequalities, prompted monetary policy to engage in periods of monetary expansion which, in turn, led to an over-accumulation of debt. Nevertheless, limited empirical evidence in Borowski et al. (2017) does not confirm the positive effect of income inequality on credit expansion in EU countries.

In order to introduce interaction between income inequality and monetary policy into standard theoretical models, heterogeneous agents need to be introduced. In Auclert (2019), heterogeneous households are characterized by different marginal propensities to consume. Additionally, households operate under different initial conditions that result in different responses to induced monetary policy shock. Areosa and Areosa (2016) distinguish agents according to their provision of labour and their access to the financial system. The group of households that do not react to monetary policy, they argue, consists of households that supply unskilled labour and that do not have access to the financial system, i.e. these households exhibit zero or only small level of bank indebtedness. As the proportion of unskilled agents increases, the number of agents directly reacting to interest rate changes decreases, which weakens the effects of monetary policy. As a consequence, even by raising interest rates to a significant extent, the monetary authorities only generate moderate effects.

This theoretical reasoning finds some support in the empirical literature. Recently, Voinea et al. (2018) show that income inequality affects the transmission of monetary policy and its effectiveness via consumption channel in Romania. Households at the lower end of income distribution are more responsive to budgetary policies and do not respond to monetary policy shocks. Monetary policy is most effective in influencing the consumption of middle income households, which are characterized by higher levels of indebtedness, owing to the fact that it eases consumption constraints on these households. High income households react to monetary policy in a lesser way than middle income households. Overall, smaller income inequality serves as an amplifier of monetary policy shocks and is conducive to a more efficient and homogeneous impact of monetary policy trans-

mission. Guerello (2018) investigated the marginal effects of standard and non-standard monetary policies on households' consumption and decomposes them to the contribution of inter-temporal and redistributive factors. According to her findings, moderate growth in income dispersion smooths the transmission mechanism of standard monetary policy because it partially offsets the intertemporal substitution component. Guerello (2018) concludes that, during normal times, moderate high-income dispersion works as an accelerator mechanism for monetary shocks. However, income distribution may become an obstacle to the smooth transmission of policy impulses in the case of zero-lower bound.

Lastly, a few studies have examined the conditional effect of monetary policy on output in presence of income inequalities. Kim (2019) reports that a higher share of low-income consumers is associated with a smaller impact of monetary policy on real output. Ma (2018) shows that a more equal economy is associated with more effective monetary policy in terms of output. Contrary to both studies, Cravino et al. (2020) do not find evidence that inequality significantly affects the response of output to monetary policy shock.

In light of the previous reasoning, the following hypotheses that reflect the demand-side oriented approach in credit market can be formulated.

A higher share of low-income individuals characterized by higher risks translates into an increased risk premium being imposed on them by loan providers. For this reason, monetary policy impulses transmitted into the loan rates of marginal low-income customers might encounter the firm lower bound if the associated risk profile of the customer has not been affected by an improvement in overall economic conditions. Additionally, low-income and risky individuals may disproportionately suffer from credit rationing, particularly during periods of severe economic downturns (Bazillier and Hericourt, 2014). As a result, even if the indirect effect of monetary transmission has materialized via better prospects in labour markets (Ampudia et al., 2018), the elasticity of response for lower-income customers may not be fully linear in comparison to middle income group. The share of liquidity-constrained individuals will therefore, put an effective cap on the bank loan rates offered to lower-income customers, thus limiting the accommodative stance of monetary policy. Empirical evidence for the euro area (Denk and Cazenave-Lacroutz, 2015) shows that the proportion

of credit-constrained households is nonlinear in income, with more than half of households in the lowest income quintile reporting that they are credit-constrained. Furthermore, the distribution of outstanding credit also resembles a non-linear function with low-income households reporting disproportionately lower level of credit exposure.

Alternatively, a higher share of middle-income earners relying on standard, bank-created, sources of financing pushes the demand for loans upward, effectively increasing loan rates, if this is not accommodated by the supply-side reaction. Yet, if cuts in key policy rates ease the interest burden of accumulated debt as well as maintain the access to bank financing (Alpanda and Zubairy, 2018), transmission of monetary policy impulses may remain unaffected or may even be magnified.

Lastly, high-income households often tend to react disproportionately to monetary policy shocks due to their lower propensity to consume (Bunting, 2009).

Additionally, the indirect channel of monetary transmission is likely to be subdued as their exposure to labour market conditions is usually limited. High-income earners also receive a portion of their income from their ownership of financial wealth (Denk and Cazenave-Lacroutz, 2015) which makes them more sensitive to financial market disruptions than to credit market developments. As a consequence, the transmission of shocks to bank loan rates in economies with a disproportional share of high-income individuals may encounter possible limitations.

3. Empirical Specification

3.1. Measuring Income Inequality

Our main variable of interest is the measure of income inequality. The most popular choice for income inequality indicator is usually the Gini coefficient (Furceri et al., 2018; Lenza and Slacalek, 2018; Voinea et al., 2018). Nevertheless, relying on the Gini index introduces a few drawbacks. Firstly and most importantly, the different shape of underlying income distribution may result in a same value of the Gini coefficient. For example, in an extreme case, an economy populated with low-, middle-, and high-income households may have the same Gini coefficient as an economy pop-

ulated with only low- and high-income households. Consequently, we argue that the use of a single indicator of income inequality might conceal two very different pictures of economic reality.¹

Alternatively, some studies define their measures of inequality differently. Bordo and Meissner (2012) use the share of income earned by the top 1-% of households. Perugini et al. (2016) also follow a similar approach, as they use the share of income earned by top 1-% of earners and the shares of the top 5-% and top 10-% as robustness checks. Perugini et al. (2016) argue that while these measures reflect the changes at the top end of income distribution, they do not reflect the changes at the bottom end. To better capture the overall shape of income distribution, Coibion et al. (2016)'s preferred measure of inequality is the difference between the income at 90th percentile and the income at 10th percentile. Expressed in terms of a ratio, Palma (2011) calculates the preferred measure of inequality as a share of income earned by the top 10-% to the share of income earned by the bottom 40-% of earners. Palma (2011) argues that the middle 50-% of earners earn approximately half of the national income, with this share being relatively stable. The rest of the national income is then divided among the top 10-% and bottom 40-% of earners – with their shares of income being rather unstable. Thus, the changes in inequality are driven by changes in the relative positions of earners at the top and at the bottom of the income distribution.

Furthermore, the Gini coefficient is very sensitive to developments in the middle of the distribution and less sensitive to developments at the tails of the income distribution (Cobham et al., 2016). Yet, the behaviour at the tails of the income distribution might be the one crucial factor impacting the effective conduct of monetary policy. The theoretical literature (Areosa and Areosa, 2016) usually relies on modelling the household sector as the one populated with two types of households with unequal access to the financial system as well as possessing different sets of skills. The share of financially excluded households is calibrated to reflect relevant empirical studies and set between 10 to 40 percent of the total population. Given the value of this pre-determined parameter, the model produces (unequal) share on income (consumption) attributed to these two distinct types

¹In model by Areosa and Areosa (2016), the same values of the Gini index g_t may arise for an unlimited number of combinations between the share of financially excluded households λ and their respective share of total consumption δ .

of households. Hence, the resulting inequality approximated by the Gini index reflects, *inter alia*, the share of financially constrained households whose response to monetary policy shocks is limited. Ultimately, the limitation of the monetary policy transmission mechanism needs to be seen in the context of those households who, due to their income profile, are only partially incorporated into the credit markets.

In order to respond to the limitations discussed above, we differ from the standard literature in the following way. Instead of measuring the income share attributed to the particular population cohort, we calculate the population share of individuals earning a particular portion of overall income. The level of income inequality is therefore reflected in an unequally shaped distribution of individuals across income progression. The resulting cross-country heterogeneity illustrates how many individuals partake in contributing to a share of income, which is normalized (i.e. equal) across countries.

Assume that income is a continuous random variable X , $f(x)$ is the income distribution and $F(x)$ is the cumulative distribution function (while $f(x) = (dF(x))/dx$). The Lorenz curve is often defined in the scholarly literature by two functions (e.g. see Gastwirth (1971)):

$$p = F(z) = \int_0^z f(x)dx \tag{1}$$

and

$$L(p) = \frac{1}{\mu} \int_0^z xf(x)dx = \frac{\int_0^z xf(x)dx}{\int_0^{\infty} xf(x)dx} \tag{2}$$

The Lorenz curve can be alternatively expressed according to Gastwirth (1971) with one equation:

$$L(p) = \frac{1}{\mu} \int_0^p F^{-1}(x) dx \quad (3)$$

Let us now denote the percentage of cumulative income earned by the bottom percentile of the population as y . If $y = L(p)$ then $p = L^{-1}(y)$. However, we are not interested in the percentage of income earned by the bottom percentile of the population; instead we aim to calculate what percentage of the population earns a particular percentage of income. For example, what percentage of the population earns the first five percentage points of income and what percentage earns the second five percentage points of income etc., while the population is ordered by the size of income. In the case of the Lorenz curve, $y \in \langle 0, 1 \rangle$ then the percentage of population earning a given percentage of income denoted as h can be calculated as the difference between the upper threshold (denoted as y^+) and the lower threshold (denoted as y^-) i.e. $h = L^{-1}(y^+) - L^{-1}(y^-)$ of the range.

Figure A1 in the Appendix plots the distribution of population shares across different income deciles for countries included in our sample. In all of the countries, the 1st decile of overall income is earned by 20-25 percent of the population. The next tenth of overall income is created by an additional 15 percent of the population. Overall, the first twenty percent of total income is earned by approximately 40 percent of the population. For the sake of this simple illustration, we term these individuals as 'poor' (or lower earners) with constrained access to the financial system. As we move along the income distribution, within the range of the 4th to 5th deciles the share of the population earning 10 percent of overall income is centered around ten percent as well. This specific location on the income distribution curve denotes the turning point, which characterizes a situation when a particular portion of the population partakes at the same share of income. Beyond this point, a smaller share of the population is needed to contribute to a tenth of overall income due to their higher average income. On the right side of the income distribution, only between two and four percent of the population is needed to earn the top ten percent of overall income. Again, these individuals might be termed as 'rich' (or higher earners) for the sake of further discussion.

To capture the steepness of the overall distribution we contrast the population shares of

individuals at the tails of the distribution, the bottom 20-% and the top 10-% of overall income. Such a measure is often used as an alternative to the Gini coefficient in empirical studies, as it is less sensitive to developments in the middle of the income distribution. The higher the *Bottom 20 %*, the poorer the poorest individuals, as more poor individuals partake one fifth of overall income. On the other hand, the smaller the *Top 10 %*, the (relatively) richer the richest individuals, as fewer high earners are needed to earn a tenth of overall income.

Figure A2 in the Appendix reports the ratio of the *Bottom 20 %* and *Top 10 %*, with an increase reflecting a steeper slope of the underlying distribution curve, hence an increase in income inequality. Several notable findings are apparent. Firstly, there exists an apparent discrepancy between the behaviour of the Gini index and the measure of the steepness of income inequality. Countries experiencing some of the biggest changes at the tails of the income distribution (Cyprus, Ireland, Belgium and Portugal) report no change in the Gini index over the years 2008-2016. Conversely, the highest increase in the Gini index is reported by Lithuania, Slovenia and Slovakia, while, at the same time, for these countries the ratio of the population shares of the poorest to the richest individuals has remained stable over time. Secondly and unsurprisingly, the ranking of countries differs for both measures. The overall trends indicate that Slovakia, Slovenia, Finland and Belgium are among the countries with the lowest inequality, while the southern EA members, along with France and Lithuania are among the countries with the highest inequality. Ranking based on Gini index differs most significantly in the case of Spain, Italy and Estonia – putting these countries at the top of the list of countries with the highest income inequality. Next, in Figures A3 and A4 in the Appendix, we plot the developments of the ratio of the *Bottom 20 %* to *Top 10 %*, and the Gini coefficient in Euro Area countries over the years 2008-2016, respectively. These plots once again confirm the existence of some differences in the developments of these two indicators of income inequality in the case of Euro Area countries.

3.2. *Econometric Model*

To estimate the effects of conventional and unconventional monetary policies conditional on income inequality, we rely on the standard PMG (pooled mean group) technique introduced

by Pesaran and Smith (1995) and Pesaran et al. (1999). This technique is widely used in studies examining the completeness of monetary policy transmission to bank lending rates (Belke et al., 2013; Illes et al., 2015; Avouyi-Dovi et al., 2017). Nevertheless, we depart from the standard interest-rate pass-through literature in the following ways.

Firstly, in order to introduce conditional effects of inequality we employ the interacted PMG estimator as used in Leroy and Lucotte (2015). Secondly, we provide three sets of different estimates varying according to different monetary policy measures (as in Horvath et al., 2018). Thirdly, we investigate the completeness of monetary policy transmission to different types of bank lending rates. In order to ensure the consistency of our estimates across different types of assets and monetary measures, the list of control variables remains unchanged across all specifications.

The benchmark interacted PMG model equation is given as:

$$\Delta r_{i,t}^b = \sum_{j=1}^p \Phi_j \Delta r_{i,t-j}^b + \sum_{j=0}^q \Pi_j \Delta r_{i,t-j}^m + \sum_{j=0}^r \Theta_j \Delta Z_{i,t-j/t-1-j} + \epsilon_{i,t} + \beta_{0,i} (r_{i,t-1}^b - \beta_1 r_{i,t}^m - \beta_2 ineq_{i,t} - \beta_3 r_{i,t}^m * ineq_{i,t} - \sum_{j=4}^u \beta_j Z_{i,t/t-1}^u - \mu) \quad (4)$$

where i denotes country, t denotes time, r_t^b represents the bank lending rate, r_t^m represents the Eonia interbank interest rate (as our proxy for standard monetary policy), μ stands for the mark-up, $ineq_{i,t}$ stands for the measure of income inequality², $Z_{i,t/t-1}^u$ represents the vector of control variables and $\epsilon_{i,t}$ is the error term.

Our primary objective is to estimate and interpret the values of the β_3 parameter that indicates the effect of our measure of income inequality on overall pass-through. The negative value of β_3 implies that the factor decreases the overall pass-through from innovations to the monetary policy variable (e.g. the Eonia r_t^m) to the dependent variable (i.e. the bank rate r_t^b).

We also calculate the total marginal effect of each monetary policy measure (henceforth TME) conditional on income inequality as a product of $(\beta_1 + \beta_3 * ineq)$. Evaluated as a minimum,

²In our case the population share of individuals earning a certain portion of overall income.

mean and maximum of the income inequality indicator, the TME measures the overall response of the dependent variable to one unit change in r_t^m in the presence of minimum, mean and maximum income inequality.

The measure of income inequality enters only the long-term equation as we hypothesise that the effects of short-term innovations to the inequality distribution are negligible. Instead, the persistent nature of the inequality-related times series favours their inclusion in the long-term relationship. From a purely technical point of view, since the data for inequality times series are available only on an annual frequency and we advocate against the use of simple extrapolation, the inequality measures are time invariant within each year. Hence, the first difference, if used, would equal zero in eleven out of twelve monthly observations per each year.

Vector $Z_{i,t/t-1}^u$ includes various control variables, as specified in the relevant literature (see Leroy and Lucotte, 2015). In our case, the list consists of variables capturing short-term business cycle elements (CDS premium, economic activity) and characteristics associated with the supply side of credit markets (bank concentration, financial system depth). The measure of inequality is assumed to represent the demand side in the relevant markets. As in the case of the inequality measure, the control variables related to the supply side in the credit market enter only the long-term part of specification due to their hypothesised long-term relationship with the dependent variable.

The follow-up specifications that aim to assess the effects of other than standard monetary policy measure extend the equation 4 in the following way:

$$\begin{aligned} \Delta r_{i,t}^b = & \sum_{j=1}^p \Phi_j \Delta r_{i,t-j}^b + \sum_{j=0}^q \Pi_j \Delta r_{i,t-j}^m + \sum_{j=0}^r \Theta_j \Delta Z_{i,t-j/t-1-j} + \sum_{j=0}^s \Lambda_j \Delta mp_{i,t-j} + \epsilon_{i,t} + \\ & \beta_{0,i} (r_{i,t-1}^b - \beta_1 r_{i,t}^m - \beta_2 ineq_{i,t} - \beta_3 mp_{i,t} * ineq_{i,t} - \beta_4 mp_{i,t-j} - \sum_{j=5}^u \beta_j Z_{i,t/t-1}^u - \mu) \end{aligned} \quad (5)$$

where $mp_{i,t}$ denotes the respective type of unconventional monetary policy measure. As in the benchmark regression, our primary objective is to estimate and interpret the values of the β_3

parameter that captures the potential effect of conditioning variables on overall pass-through. The hypothesised value of the β_3 parameter differs depending on the measure of the monetary policy tool. In the case of quantity-based indicators (e.g. QE/GDP), the positive β_3 parameter will indicate a decrease in overall pass-through as β_4 is hypothesised to obtain negative values.

Similarly, we calculate the TME of unconventional monetary policy measures conditional on income inequality as a product of $(\beta_4 + \beta_3 * ineq)$. Evaluated as a minimum, mean and maximum of income inequality indicator, the TME measures the overall response of the dependent variable to one unit change in $mp_{i,t}$ in the presence of minimum, mean and maximum income inequality.

3.3. Rolling Windows Approach

Some measures of income inequality focus on the tails of income distribution rather than its overall shape (Palma, 2011; Bordo and Meissner, 2012; Perugini et al., 2016; Coibion et al., 2016). However, in these cases the choice of specific percentiles is somewhat arbitrary without any empirical or theoretical justification. In our case, highly disaggregated micro data from the EU-SILC database allows us to derive measure of inequality capturing the steepness of the underlying distribution without any *prior* assumption regarding the population share of the poorest or richest individuals who (do not) respond to monetary policy shocks. In order to take advantage of the available micro data, we employ the rolling window regression approach in the following way.

In the initial step of our analysis, we split income distribution into individual percentiles (of overall income) with an associated population share of individuals, as described in sub-section 3.1. We then aggregate the individual percentiles into income groups (i.e. the window size) in order to increase the stability of the estimated coefficients and run the regressions, as described in equations 4 or 5, by moving along the income distribution using a set of pre-determined step and window sizes.³ The results from individual regressions are stored and presented in the form of a histogram, plotting the frequency of statistically significant results for the interaction term in specification 4, or 5 respectively, per individual percentiles. The total marginal effects for individual percentiles

³The different combinations of step and window sizes that we used include 2 and 6, 3 and 10, 3 and 13, 4 and 8, and 5 and 10, respectively.

are plotted in the form of boxplots capturing distribution of estimated and statistically significant TMEs across all specifications.

Based on the results from the first stage of our analysis, we proceed with creating an aggregate indicator of income inequality. As we discuss in section 2 and sub-section 3.1, the transmission of monetary policy impulses is hypothesised to crucially depend on the split between individuals with constrained access to the financial system and financially included individuals. In the second stage of our analysis we therefore construct individualized measure of income inequality as a ratio of the population share of low earners to the population share of higher earners⁴, separately for each dependent variable (i.e., consumer, housing, small firm and large firm loan rates) and for each measure of monetary policy. The exact split is derived so that it reflects the statistically and economically significant results associated with the interaction term from equations 4, or 5. The more unequal the income distribution, the higher the resulting inequality indicator and the more limited monetary transmission mechanism.

Furthermore, we also demean data for the population shares for each year and keep the demeaned values only for the 25 % countries with highest and 25 % countries with lowest values, i.e. 1st and 4th quartiles. The values for the remaining countries in the middle of the cross-country distribution are hard-set to zero. This decision is motivated by the following considerations. Firstly, we magnify the limited heterogeneity among EA members by comparing the observations located on both ends of the cross-country distribution while discarding the progression in the middle. Additionally, we investigate the effect of the *relative* distance across countries rather than the impact of absolute size of income inequality. This is all the more important due to the fact that, as discussed in sub-section 3.1, our measure of inequality is, by definition, anchored to a specific combination of income share and associated share of population.⁵ By demeaning the data, we implicitly assume that countries in the middle of the cross-country distribution are relatively equal

⁴Our approach is thus related to the approach of Palma (2011), who defined his measure of inequality as a ratio of the income shares of the top 10-% and bottom 40-% of earners – i.e. the inequality is measured as the ratio of higher and lower earners.

⁵I.e. in the case of splits into income deciles, complete equality is achieved if exactly ten percent of the entire population earns ten percent of income. The locking point depends on the choice of scale used to split underlying income distribution.

on average, even if in absolute terms, they still may be considered highly unequal societies.

While this approach enables us to magnify the effects of income inequality by focusing only on countries with the highest and lowest inequality, it could be argued that, due to the rather persistent nature of this indicator, our results are predominantly driven by the same set of countries. Nevertheless, on closer inspection, we observe that across the different inequality indicators and years, the composition of the 25 % most unequal and 25 % most equal countries varies; with eleven of the fifteen EA member states from our sample falling among the top or bottom 25 % for at least one income inequality indicator and one year.⁶

Among our countries, there exists a group of 'switchers' whose position improves (or worsens) over time and, as a result, these countries remain in either the 1st or 4th quartile for only a short period of time. These countries predominantly include Estonia and Portugal, with other countries also showing at least some extent of variation (Cyprus, Finland, France, Lithuania, the Netherlands). Additionally, there is no clear pattern apparent among neither the most nor the least equal societies. In general, Belgium, Slovakia, Slovenia, Finland and the Netherlands form a group of the most equal economies (i.e. these countries can be found in the first quartile, that is 25 % of countries with the lowest inequality), while Estonia, Lithuania, Portugal, and Spain are often found among the countries with the highest income inequality (i.e. the fourth or last quartile). Heterogeneous in terms of size, economic development or geographical location, the income inequality indicator is hypothesised to add a new piece of information uncovering the roots of the heterogeneous impact of the common monetary policy in EA member states.

3.4. Data

We use monthly data for the period between January 2008 and December 2016 for a panel of 15 Euro Area (EA) countries.⁷ Our dataset starts on the eve of the Global Financial Crisis of 2008-2009 (GFC), which allows us to discard possible shift in monetary pass-through due to the crisis

⁶We have constructed transition matrices, which display the countries that make up the 25 % highest and 25 % lowest observations for each inequality indicator for each year. These matrices are available upon request.

⁷Austria, Belgium, Cyprus, Estonia, Finland, France, Germany, Ireland, Italy, Lithuania, the Netherlands, Portugal, Slovakia, Slovenia, and Spain.

events, as observed in several studies (Hristov et al., 2014; Aristei and Gallo, 2014; Gambacorta et al., 2015).

The European Union Statistics on Income and Living Conditions database (henceforth EU-SILC) provides microdata on income, living conditions, poverty, and social inclusion for both households and individuals for all the EU countries as well as Norway and Switzerland. The EU-SILC data are collected as a sample survey annually – based on nationally representative probability samples – with the overall EU-wide sample covering more than 200,000 individuals and 100,000 households. Due to the limitations on data availability from the database our sample ends in 2016. While restricting our sample, this allows us to investigate the first-round effects of the QE policies that are hypothesised to become more subdued as time progresses.

Most studies that investigate the relationship between monetary policy and income inequality rely on gross income data – as this makes it possible to ignore the potential impact of national distributional fiscal policies, which have contributed to changes in disposable income (Domanski et al., 2016). We depart from this approach and use disposable income instead. Households' access to credit is ultimately influenced by their level of disposable rather than gross income, i.e., it is disposable income that a bank considers when assessing an individual loan application.

As our dependent variables, we use interest rates on bank loans to households and firms: these include interest rates on four main loan categories – consumer and housing loans to households, as well as interest rates on small and large (below and above 1 million EUR) loans to non-financial corporations (NFCs). The interest rates are for new business and all the data are from the ECB. We plot the development of the four types of bank loans rates for all the countries in our sample in Figure A5 in the Appendix. This plot indicates the existence of heterogeneity in the development of different types of bank loans rates across the Euro Area countries.

In line with other studies (von Borstel et al., 2016; Horvath et al., 2018) we use the EONIA rate as a proxy for standard monetary policy. The EONIA rate is expressed as a monthly average and the data were obtained from the ECB. The effects of unconventional monetary policies are usually studied and approximated by an increase in central bank balance sheets (Boeckx et al., 2017; von Borstel et al., 2016). However, as argued by Horvath et al. (2018), the use of total

central bank balance sheet value mixes together two distinct categories of central bank balance sheet policies – the effect of pure quantitative easing conducted via the purchase of government securities (QE henceforth), and the effect of credit easing policies that may not necessarily lead to an overall increase of total central bank assets (CE henceforth). In our approach, we build upon Horvath et al. (2018) and separate these two channels by distinguishing between QE policies and other unconventional monetary policy tools (open market operations, purchase of other than government bond securities). Consequently, as our measure of QE policies, we use the total holdings of government debt securities of respective national central banks (NCBs). Our measure of other unconventional monetary policies (i.e. CE policies) contains debt securities issued by Monetary Financial Institutions (MFIs) that are held by NCBs and the outstanding loans of NCBs to MFIs.⁸ The data on NCBs’ balance sheet items are from the ECB Statistical Data Warehouse. Both variables are expressed as a share of GDP.

Alternatively, the use of the shadow bank rate as a proxy for the overall stance of monetary policy in times of zero-lower bound has found many proponents (Horvath et al., 2018; de Polis and Pietrunti, 2019). Additionally, Samarina and Nguyen (2019) used the shadow rate to study the effect of monetary policies on income inequality. The advantage of using shadow rates is that they capture both standard and non-standard monetary policies (including forward guidance). Furthermore, shadow rates are not constrained by zero lower bound, but their estimation is also associated with some uncertainties. Consequently, we also use the shadow rate as a measure of overall expansionary monetary policy. The data on the shadow rate for the Euro Area are taken from Wu and Xia (2016).

Finally, we also introduce several control variables into our regressions to control for other factors that may affect our dependent variables. These include sovereign CDS premia obtained from the Datastream database in order to control for sovereign credit risk (Horvath et al., 2018). We also control for the country-level macroeconomic environment and possible pro-cyclical behaviour of bank rates stemming from an increase in demand during output booms (Sørensen and Lichten-

⁸For further discussion on the differences between quantitative easing and credit easing policies, see Smaghi (2009).

berger, 2007). However, in order to keep the number of explanatory variables limited,⁹ we create a composite measure of macroeconomic development by principal component analysis. This composite measure integrates the index of industrial production (as our proxy for economic performance), the harmonized index of consumer prices and the economic sentiment indicator from the Eurostat.¹⁰

A second group of control variables is taken from the IRPT literature recently summarized in Gregor et al. (2019). Using a meta-analysis approach, Gregor et al. (2019) show that the completeness of the IRPT to bank lending rates is positively affected by the depth of the financial system, as well as by the history of central bank independence. Leroy and Lucotte (2015) find that, in addition to cyclical factors, the level of banking competition plays a prominent role in hindering the homogeneity of the IRPT in Europe. Our set of control variables, thus, includes an indicator for bank concentration, which is calculated as the share of total assets of the banking sector held by the three largest banks, and a measure of financial system development, which we proxy with the credit to GDP ratio from the World Bank’s Global Financial Development Database. Bank concentration enters regressions as a contemporaneous determinant, and credit market depth with a one-year lag to mitigate potential multicollinearity.

Table 1: Summary Statistics

Variable	Unit	Obs	Mean	St. Dev.	Min	Max
Consumer loans rates	%	1,374	7.53	3.31	2.87	22.54
Housing loans rates	%	1,399	3.35	1.10	1.12	7.28
Small firm loans rates	%	1,399	4.04	1.41	1.70	8.08
Large firm loans rates	%	1,399	2.95	1.38	1.02	7.25
EONIA	%	1,399	0.48	0.98	-0.35	4.30
CE	%	1,399	67.40	61.62	3.23	338.49
QE	%	1,399	25.13	19.03	0.00	107.97
Shadow rate	%	1,399	-0.64	1.86	-4.57	4.28
CDS premium	b.p.	1,399	146.14	172.35	9.00	1399.09
PCA real economy	Score	1,399	-0.38	1.21	-4.67	2.44
Credit to GDP	%	1,399	102.88	48.08	40.52	260.70
Bank concentration	%	1,399	72.59	12.89	44.93	97.74

⁹The higher number of explanatory variables caused problems with the estimation of our regressions due to collinearity issues.

¹⁰All these three variables enter the principal components analysis expressed as logarithms.

We report the summary statistics for bank loan rates (i.e. dependent variables), measures of monetary policies and the control variables in Table 1. The summary statistics indicate that, among bank loan rates, consumer loans rates exhibit the highest average values, followed by small firm loans rates, housing loans rates and large firm loans rates. Consumer loans rates are also characterized by the highest heterogeneity. The average value of the EONIA interbank rate, our proxy for standard monetary policy, was approximately 0.5-%, while the shadow rate, our proxy for the overall expansionary monetary policy stance, averaged at -0.6-%. For credit easing policies and QE policies, we observe the average values of 67-% and 25-% of GDP, respectively.¹¹ However, the values for CE policies are characterised by much higher heterogeneity. This is due to the fact that the volume of QE was distributed among EA members according to the ECB capital key, while CE policies were provided to the banking sector without any pre-determined limits. Finally, the EA member states included in our sample have rather concentrated banking systems, as the three largest commercial banks control, on average, almost 73-% of total commercial banking assets. The EA member states also exhibit high rates of financial development with the credit-to-GDP standing at slightly more than 100-%. Nevertheless, there is also quite a significant cross-country heterogeneity with regards to the credit-to-GDP ratios.

Before proceeding with the estimation of our baseline regressions, we conduct panel unit root tests to assess the order of integration. To save space space, we do not report the results of these tests, but the results of the unit root tests and the panel cointegration test results by Westerlund (Westerlund, 2005) are available upon request. According to the results, our regression specifications indicate the presence of cointegration as in most of the cases we are able to reject the null hypothesis of no cointegration.

¹¹This somehow surprising difference between the average values of QE and CE policies is caused by the fact that the QE policies were only introduced at the end of our sample in 2015 leading to lower average value for the entire sample compared with CE policies.

4. Results

In the following section, we discuss the findings of the rolling window regressions, specifications with aggregate inequality measure and several robustness checks.

4.1. Rolling Windows Regressions

In the first step of our analysis we aim to empirically evaluate the response of the dependent variables (i.e., bank loans rates) conditional on the share of the population earning a certain portion of income across the entire income distribution by using the rolling windows approach. To increase the robustness of the results of the rolling windows regressions, we use several different combinations of step and window sizes that we run separately. Figures A6, A7, A8 and A9 in the Appendix report findings from individual regressions using the rolling-window approach as described in section 3.3. Each figure plots the distribution of TMEs for each percentile of income evaluated at the minimum and maximum values of *ineq*, along with a measure of the frequency of statistically significant instances of interaction term in the respective rolling windows regressions.

As expected, in many cases we are able to identify one dominant turning point that signifies a break in the unequal contribution of individuals to overall income, conditional on the type of the monetary policy measure and dependent variable (see the discussion in sub-section 3.1).

Overall, we find that income inequality seems to play an important role in the transmission of standard monetary policies to bank loans rates, especially in the consumer loans segment (Figure A6). For consumer and housing loan rates, we find that the smaller share of low-earning individuals contributing to the bottom end of income distribution (pointing to lower inequality) improves the transmission of standard policies to consumer and housing loans rates. In the former case, the difference between the relatively most equal and unequal countries is also economically significant and the turning point is found to lie close to the 4th decile. Statistically speaking, significant results are concentrated at the lower bottom end and higher upper end of the distribution rather than in the middle. This highlights the fact that for efficient monetary transmission, the behaviour at the tails of the income distribution matters more.

In the case of firm loans, this segment might be understood more as a control group, which is less affected by underlying income distribution. This is apparent particularly in the case of large firm loans where the impact of income inequality on monetary policy transmission is on the one hand, statistically significant, but, on the other hand, economically negligible. The small firm loans rates are sensitive to income inequality concentrated in the lowest part of the distribution (1st decile). However, the most pronounced effect of income inequality is observed from the 3rd decile upward, suggesting that the higher equality of income of the middle and upper class individuals promotes more efficient pass-through to small firm loans rates.

For non-standard monetary policies, we report the total marginal effects capturing the strength of transmission in Figures A7 and A8 in the Appendix. While similar in their ultimate objective, both measures differ in terms of conduct, with CE policies aiming to ease credit constraints and directly support credit provisioning, whereas QE primarily targets the long-term bond yields.

In the case of CE policies, the statistically and economically significant share of the population is often located in the upper parts of the income distribution around the 9th decile. Apparently, this very specific segment of the richest individuals has served as either an amplifier (consumer and small firm loans rates) or a limiting factor, dampening the effects of CE policy shocks (housing loans, large firm loans). Whereas in the first case, the higher level of inequality is associated with an improvement in monetary transmission, the latter case exhibits the opposite effect. Interestingly, in the case of housing and large firm loans rates, we observe over the last decade the presence of a 3rd distinct group located around the 8th decile, which may be described as the upper middle class. As evidenced, the more populated this group, the smaller the transmission of shocks to the given bank loan rates. One possible explanation for this may be related to this group's relatively higher level of indebtedness (Denk and Cazenave-Lacroutz, 2015) which, while positively affected by the easing of credit constraints, still puts a binding cap on the extent of the effect of possible monetary loosening (Alpanda and Zubairy, 2018).

The effect of quantitative easing policy is, unsurprisingly, susceptible to the selection of dependent variable and differs substantially across the underlying income cohorts (Figure A8 in the Appendix). The turning point in the three types of bank loans (housing, consumer, small firm) is

located around the 3th decile, whereas for the large firm loans rate, the turning point seems to be closer to the left side of the income distribution (1st decile). A higher population share of poorer individuals, i.e. higher inequality, is once again more conducive to efficient monetary transmission in the case of consumer and small firm loans, while the relationship is completely opposite in case of housing and large firm loans. As in the case of CE policies, the behaviour of housing loans interest rates reveals the possible presence of not only two distinct types of individuals (i.e. financially constrained versus fully financially included), but also the existence of a third group of possibly over-leveraged individuals. According to our results, the higher population share of individuals earning the 7th to 9th decile of income may substantially hinder the overall effectiveness of the monetary transmission of QE policies.

Finally, in Figure A9 in the Appendix we report the results with shadow rate that integrates all three distinct monetary policy tools into one comprehensive measure.¹² As in the case of the EONIA, an increase in the total marginal effects plotted in A9 indicates an improvement in interest rate pass-through, hence amplifying the overall transmission mechanism in presence of underlying income inequality. In general, the results for some categories (housing loans, small firm loans) are more stable, however they tend to conceal the diverse effects of individual unconventional monetary tools as they often follow the pattern observed for standard monetary policy.

As in the case of the EONIA, housing loan interest rates are more responsive towards policy shocks in countries with more populous groups of richer individuals (i.e. financially included), than in economies populated by higher shares of financially constrained individuals. For consumer loans rates, the economically highest impact of income inequality is observed in the lowest parts of income distribution – generally favouring smaller shares of financially constrained individuals. This trend is magnified by the behaviour in the upper parts of the distribution (9th decile) with a smaller share of the population earning top income percentiles seemingly being supportive of efficient monetary transmission, which is also the case for the more populous middle income group (around the 5th decile).

¹²Additionally, the shadow rate also entails other unconventional policies - forward guidance, for example.

Statistically and economically, the most significant results for small firm loans interest rates are concentrated in the lower part of the distribution, thus favouring countries populated with fewer financially constrained individuals (with the exception of the lowest part of the distribution up to the 5th percentile). We observe a similar pattern in the large firm loans segment, with additional empirical evidence pointing to a statistically, as well as an economically prominent positive effect, of a highly concentrated share of richer individuals on overall IRPT.

4.2. Regressions With One Single Inequality Measure

As discussed in section 3.3, we now proceed with presenting our empirical findings from models incorporating one single measure of income inequality - the ratio of a population share of 'poorer' individuals concentrated on the left side of the income distribution and the population share of 'richer' individuals located on the right side of the underlying income distribution. The final selection of respective percentiles representing these two distinct groups of the population is reported for all specifications.¹³

We include our measures of income inequality in equations 4 and 5 and report these results in Tables 2 and 3. In general, our findings suggest that income inequality does play a role in the transmission of monetary policy impulses into bank loan rates, albeit with a heterogeneous impact depending on the type of bank loans and monetary policy measure used. The long-term pass-through for the standard monetary policy measure (EONIA) varies from partially incomplete (consumer loans) and almost complete (large firm loans) to even highly elastic responses (housing and small firm loans). These findings are in line with other relevant studies reporting a complete IRPT for business loans (Horvath et al., 2018; Belke et al., 2013), but we differ in estimating the statistically significant presence of the almost complete IRPT for both types of household loans. However, consumer loans rates still record the smallest IRPT out of all the categories, confirming findings in other relevant papers (Aristei and Gallo, 2014). Long-run IRPT exceeding unity is also not exceptional and was reported in papers such as Marotta (2010) and da Silva Rocha (2012).

¹³For example, for the combination of consumer loans rates and the EONIA, we define our measure of inequality as the ratio of the share of the population earning the income from the 20th to the 35th percentile of total income to the share of the population earning a total income from the 70th to the 100th percentile.

Unconventional monetary policies reduce bank loans rates over the longer term in the case of CE policies (consumer loans), as well as in the case of QE policies (housing loans rates, small firms loans rates). QE also leads to a decrease in bank rates over the short-term in the housing and large firms loans rates. However, contrary to expectations, the opposite sign is reported in the case of consumer loans rates (QE) and firm loans rates (QE, CE). Our findings may, thus, partially support arguments warning against the adverse effects of a too-low-for-too-long environment due to loose monetary policy (Horvath, 2017).

When using the the shadow rate as monetary policy measure, we find a highly incomplete pass-through, pointing out the limited effects of monetary policy (both standard and non-standard) in the aftermath of the liquidity crisis of 2008-2009 and subsequent period of negative interest rates. As Horvath et al. (2018) do not find evidence of an adverse effect of negative key policy rates on the overall transmission mechanism, we attribute this finding to the rather subdued performance of unconventional policy tools integrated into the shadow rate.

Turning our attention to our main variable of interest, the income inequality indicator, we find evidence that income inequality not only exerts significant influence over monetary transmission, but also often seems to affect the overall level of bank loan rates.

Table 2: The role of income inequality in the transmission of monetary policy to consumer and housing loans rates

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Consumer loans rates					Housing loans rates				
<i>Long-run equation</i>										
EONIA	0.959*** (0.164)	0.677*** (0.152)	0.846*** (0.119)	0.984*** (0.138)		1.264*** (0.063)	1.249*** (0.059)	1.274*** (0.063)	1.199*** (0.054)	
CE			-0.003** (0.002)					-0.002 (0.002)		
QE				0.009*** (0.003)					-0.010*** (0.004)	
Shadow rate					0.498*** (0.063)					0.766*** (0.038)
CDS premium	0.002*** (0.001)	0.001 (0.001)	0.002** (0.001)	0.000 (0.001)	0.000 (0.000)	0.004*** (0.000)	0.004*** (0.000)	0.005*** (0.000)	0.004*** (0.000)	0.003*** (0.000)
PCA real economy	0.524*** (0.122)	0.197* (0.116)	0.223* (0.125)	0.058 (0.162)	0.218** (0.107)	0.341*** (0.056)	0.317*** (0.052)	0.392*** (0.058)	0.359*** (0.053)	0.653*** (0.073)
Bank concentration (%)	0.115*** (0.017)	0.007 (0.013)	0.021 (0.015)	-0.010 (0.015)	0.015 (0.015)	-0.010*** (0.003)	-0.009*** (0.003)	-0.009*** (0.003)	-0.005** (0.002)	-0.006 (0.005)
Credit to GDP (%)	-0.017*** (0.004)	-0.024*** (0.004)	-0.018*** (0.005)	-0.026*** (0.005)	-0.031*** (0.004)	-0.002 (0.001)	0.000 (0.001)	-0.000 (0.002)	-0.003** (0.001)	-0.005*** (0.002)
Income inequality		10.895*** (0.939)	3.855*** (0.836)	16.239*** (2.126)	19.931*** (1.309)		-0.202 (0.192)	0.130 (0.204)	-3.400** (1.620)	-0.057 (0.182)
Interact		-1.549** (0.782)	0.007 (0.012)	-0.129 (0.116)	-0.721 (0.468)		-0.147 (0.097)	-0.005* (0.003)	0.161** (0.065)	-0.176*** (0.055)
Constant	-0.008 (0.973)	8.879*** (0.889)	7.536*** (0.972)	9.912*** (1.039)	9.762*** (0.764)	2.517*** (0.264)	2.293*** (0.323)	2.300*** (0.287)	2.745*** (0.235)	3.930*** (0.387)
<i>Short-run equation</i>										
Error correction	-0.077 (0.054)	-0.119* (0.068)	-0.108* (0.065)	-0.123* (0.071)	-0.138* (0.077)	-0.055*** (0.011)	-0.057*** (0.013)	-0.053*** (0.011)	-0.070*** (0.016)	-0.048*** (0.010)
D.EONIA	-0.792 (0.797)	-0.611 (0.646)	-0.769 (0.831)	-0.731 (0.794)		0.237*** (0.063)	0.221*** (0.059)	0.253*** (0.066)	0.226*** (0.074)	
D.CE			-0.000 (0.003)					0.000 (0.000)		
D.QE				0.000 (0.008)					-0.006** (0.003)	
D.Shadow rate					-0.073 (0.055)					0.000 (0.012)
D.CDS premium	0.006 (0.005)	0.005 (0.004)	0.005 (0.004)	0.005 (0.004)	0.004 (0.003)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
D.PCA real economy	0.112 (0.211)	0.100 (0.208)	0.111 (0.204)	0.108 (0.205)	0.089 (0.214)	0.006 (0.019)	0.007 (0.018)	0.005 (0.020)	0.004 (0.019)	0.009 (0.022)
Ineq measure def		20-35/ 70-100	13-22/ 83-100	10-20/ 53-65	8-26/ 42-70		5-18/ 76-95	1-10/ 75-90	1-13/ 14-66	10-30/ 75-100
Observations	1,373	1,373	1,373	1,373	1,373	1,399	1,399	1,399	1,399	1,399

Notes: Interact is defined as the interaction term of the EONIA, CE, QE and the shadow rate and our measure of inequality, which is defined specifically for each dependent variable and for each measure of monetary policy. CE stands for credit easing policies, QE for quantitative easing policies. The measure of income inequality is expressed as a ratio of the population share of poorer individuals earning a certain percentage of income to the population share of richer individuals earning a certain percentage of income – so an increase in the value of this measure means an increase in income inequality. The exact values based on which these respective measures were calculated are reported in the row *Ineq measure def*. Standard errors are in parentheses. * indicates significance at the 10% level, ** at the 5% level and *** at the 1% level.

Table 3: The role of income inequality in the transmission of monetary policy to large firm and small firm loans rates

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Small firm loans rates					Large firm loans rates				
<i>Long-run equation</i>										
EONIA	1.355*** (0.094)	1.185*** (0.078)	1.389*** (0.101)	1.313*** (0.088)		0.913*** (0.018)	0.912*** (0.024)	0.915*** (0.012)	0.922*** (0.015)	
CE			0.002 (0.003)					0.002*** (0.001)		
QE				-0.010* (0.006)					0.012*** (0.001)	
Shadow rate					0.601*** (0.036)					0.504*** (0.034)
CDS premium	0.007*** (0.001)	0.007*** (0.001)	0.008*** (0.001)	0.008*** (0.001)	0.003*** (0.000)	0.003*** (0.000)	0.003*** (0.000)	-0.000 (0.000)	0.001*** (0.000)	0.002*** (0.000)
PCA real economy	0.377*** (0.085)	0.247*** (0.075)	0.399*** (0.085)	0.420*** (0.077)	0.625*** (0.071)	0.071*** (0.015)	0.058*** (0.013)	0.083*** (0.012)	0.077*** (0.014)	0.641*** (0.055)
Bank concentration (%)	0.025*** (0.003)	0.021*** (0.003)	0.013*** (0.004)	0.014*** (0.003)	0.032*** (0.005)	-0.001 (0.001)	-0.007*** (0.002)	-0.010*** (0.002)	-0.003 (0.002)	0.021*** (0.005)
Credit to GDP (%)	0.009*** (0.002)	0.003 (0.002)	0.011*** (0.003)	0.013*** (0.002)	0.011*** (0.001)	0.000 (0.001)	-0.003*** (0.001)	0.006*** (0.001)	0.006*** (0.001)	0.014*** (0.001)
Income inequality		-0.186* (0.102)	0.254*** (0.057)	2.277*** (0.789)	1.713*** (0.239)		-1.074*** (0.230)	-0.070*** (0.021)	-0.441 (0.327)	1.208*** (0.273)
Interact		0.621*** (0.188)	-0.006*** (0.002)	-0.147*** (0.039)	0.157 (0.108)		0.067 (0.198)	0.001 (0.000)	0.017 (0.019)	-0.178 (0.114)
Constant	-0.425 (0.328)	0.498 (0.310)	-0.062 (0.424)	0.274 (0.370)	0.094 (0.367)	1.631*** (0.127)	2.279*** (0.162)	1.838*** (0.121)	1.112*** (0.119)	-0.327 (0.383)
<i>Short-run equation</i>										
Error correction	-0.111** (0.048)	-0.141** (0.063)	-0.108* (0.057)	-0.150* (0.079)	-0.092*** (0.026)	-0.250*** (0.051)	-0.238*** (0.062)	-0.213*** (0.052)	-0.265*** (0.060)	-0.183*** (0.054)
D.EONIA	0.123 (0.226)	0.083 (0.269)	0.071 (0.283)	0.094 (0.265)		0.190 (0.134)	0.429*** (0.131)	0.562* (0.307)	0.324* (0.168)	
D.CE			0.001 (0.001)					0.003** (0.002)		
D.QE				-0.002 (0.003)					-0.024* (0.013)	
D.Shadow rate					0.002 (0.021)					-0.026 (0.043)
D.CDS premium	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.002 (0.001)	-0.001 (0.000)	0.000 (0.001)	0.001 (0.002)	0.002 (0.002)	0.001 (0.001)	-0.000 (0.000)
D.PCA real economy	0.024 (0.041)	0.034 (0.037)	0.018 (0.032)	0.034 (0.036)	-0.001 (0.037)	0.134** (0.066)	0.132** (0.062)	0.101* (0.053)	0.128* (0.066)	0.043 (0.039)
Ineq measure def		1-12/ 66-80	8-39/ 82-100	1-21/ 36-90	1-5/ 65-80		1-16/ 43-74	1-11/ 89-100	9-25/ 71-95	10-25/ 60-70
Observations	1,399	1,399	1,399	1,399	1,399	1,399	1,399	1,399	1,399	1,399

Notes: Interact is defined as the interaction term of the EONIA, CE, QE and the shadow rate and our measure of inequality, which is defined specifically for each dependent variable and for each measure of monetary policy. CE stands for credit easing policies, QE for quantitative easing policies. The measure of income inequality is expressed as a ratio of the population share of poorer individuals earning a certain percentage of income to the population share of richer individuals earning a certain percentage of income – so an increase in the value of this measure means an increase in income inequality. The exact values based on which these respective measures were calculated are reported in the row *Ineq measure def*. Standard errors are in parentheses. * indicates significance at the 10% level, ** at the 5% level and *** at the 1% level.

In the case of consumer loans rates, this segment is hypothesised to be affected by underlying inequality to the highest extent, as this particular loans segment is often used to overcome short-term liquidity constraints faced by households and enables them to smooth their individual consumption. Across all specifications, we find that households living in highly unequal societies encounter substantially higher consumer loans rates. This observation may reflect the higher risk premium faced by lower earners, as well as the associated asymmetric information issue (Aristei and Gallo, 2014). On top of that, the transmission of monetary impulses has been significantly limited by increasing income inequality in the case of standard monetary policy, whilst unconventional monetary policies do not seem to be affected by underlying heterogeneity. Thus, their relative success has not been strongly influenced by the underlying income heterogeneity across the EA member states.

Income inequality also seems to matter in the case of the average bank rate on housing loans with regards to the transmission of unconventional monetary policies. While a more unequal society enhances the transmission of CE policies, the effects of QE policies tend to be limited by a more heterogeneous income distribution. Interaction with the shadow rate (specification [10], Table 2) is also statistically significant, however, the response is likely to be driven by the quantitative easing policy element, as documented by the findings in the specifications in [8] and [9]. Confirming the initial hypothesis, we conclude that higher income inequality with more credit constrained individuals and/or over-leveraged richer individuals lowers the overall response towards quantitative easing policies. On the other hand, the transmission of standard monetary policy to housing loans rates does not seem to be affected by income heterogeneity.

In Table 3, we report the results of regressions studying the role of income inequality on the transmission of monetary policies to small and large firm loan rates. Rather surprisingly, small firm loans rates seem to be highly affected by income inequality, both by the level of inequality proxied by our inequality ratios and by the role that inequality plays in the transmission of monetary policies. As in the case of consumer loans, the shape of income distribution tends to matter for the overall level of loan rates with, in general, higher inequality leading to higher small firm bank loan rates. Yet, this impact seems to be mitigated by the conditionality of monetary transmission, with

more unequal societies being more responsive towards looser monetary policy, both standard and non-standard.

Small and medium enterprises (SMEs) in Europe constitute 99.8-% of all businesses, contribute to 54.6 % of total value added and provide employment for 67-% of the total active labour force, out of which 2/3 are created in micro and small firms sector with fewer than 50 employees (EC, 2019). Yet, studies consistently show that wages in this sector are smaller in comparison to those paid in large companies (Oi and Idson, 1999). On top of that, studies focusing on self-employed entrepreneurs often document lower than-average incomes for a large section of the self-employed workforce (Halvarsson et al., 2018). As a result, a stronger elasticity of response in the small firm loans rates segment in the presence of higher inequality with a population more concentrated at lower income deciles may reflect the empirical association between more prevalent employment in SMEs and associated lower average income. In other words, the small firm loans segment is more likely, on average, to be responsive towards monetary shocks in countries with a higher share of the population employed in SMEs possibly earning lower wages.

Lastly, we do not find any effect of income inequality on the transmission of either standard or non-standard monetary policies to large firm loan rates. This finding is broadly in line with our theoretical expectations, namely, we would expect income inequality to play a more significant role in the transmission of monetary policies to consumer and housing loans (i.e. loans provided to households) rather than large firm loan rates.

As expected, we report that higher a sovereign credit risk is associated with higher bank interest rates across all specifications, as already shown in Leroy and Lucotte (2015) and Horvath et al. (2018). Additionally, positive growth prospects approximated by the composite measure of real economic activity result in an increase in bank loan rates in all loan categories. Similar results were reported in Sørensen and Lichtenberger (2007) for mortgage loan rates in the Euro Area. The effect of two control variables representing the supply side of credit markets is somewhat heterogeneous depending on the particular loan segment. In general, more developed banking systems contribute positively to lower bank loans rates for household loans (i.e. consumer and housing loans), yet they have an adverse effect on the price of loans to non-financial corporations. Bank concentration

also plays an expected role in the case of small firm loans, yet its effect in case of consumer and large firm loans is ambiguous. For the housing loans segment, a higher concentration might even benefit customers by lowering overall loan rates. These results are not so contradictory as the absence of the effect of bank competition on bank interest spreads has also been reported by van Leuvensteijn et al. (2008) for long-term loans to enterprises and by Sørensen and Lichtenberger (2007) for mortgage bank loans. A negative relationship between concentration and bank loan rates may also highlight the validity of the “efficient-structure hypothesis” which suggests that concentration may even increase the overall efficiency of the sector (Gropp et al., 2007).

From a policy point of view, our findings indicate the relevance of income inequality for the transmission of monetary policy, as hypothesised in Voinea et al. (2018). This is apparent, in particular, in the consumer loans rates segment and for the effectiveness of standard monetary policy IRPT, thus providing empirical evidence likely to support the theoretical reasoning posited in Krueger and Perri (2006). Observed empirical turning point, set between the 3rd – 4th decile, also seems to be in accordance with the calibration used in the DSGE models with heterogeneous agents (Areosa and Areosa, 2016).

Secondly, a more elastic response in the case of small firms operating in relatively highly unequal societies also raises an intriguing question regarding the link between income inequality and the funding opportunities of the SMEs. On the one hand, our findings may constitute a positive message for policymakers as our findings indicate a higher sensitivity towards monetary policy shocks, particularly in societies that may suffer from the negative consequences of higher income inequality. On the other hand, one should take into consideration the potential causal effect of SMEs’ activities on widening income gaps (Atems and Shand, 2018), which is likely to be magnified by looser monetary policy.

Thirdly, our rolling-window regression approach identifies, in several instances, more than two distinct groups of the population in terms of their conditional effect on monetary transmission. On the one hand, this finding supports the argument towards the use of models with heterogeneous agents. However, it seems to argue against the use of a too-simplistic structure describing the population, especially in the case of unconventional monetary tools and loans serving those with

financial needs of a long-term nature. Apparent particularly in case of housing loans, further research on the distribution of banking debt and associated financial wealth may shed more light on this issue, as in Alpanda and Zubairy (2018).

4.3. Robustness checks

In the first robustness check, we address potential endogeneity concerns stemming from interlinkages between bank loan rates, i.e. bank debt costs for customers, and level of income inequality by fixing the measure of inequality at 2008 levels (i.e. the first year of our sample and the year when the GFC began). The time-invariant nature of the inequality measure also alleviates potential multicollinearity issues on the right-hand side of equations 4 and 5. The introduction of the time-invariant inequality measure leads to its removal from the long-term part of specification in 4 (5), with only the interaction term remaining. The obtained results, available upon request, confirm the adverse effects of inequality on monetary transmission in the consumer loans segment not only for standard, but also for unconventional tools. The impact of income inequality is also confirmed in the case of housing loans, with higher inequality leading to less effective monetary transmission in the case of standard policies, but with a positive effect in the case of QE and CE policies. Overall, the unresponsiveness of large firm loan rates remains unchanged when compared to the benchmark results – with the exception of CE policies. We also find a significant conditional response of small firm loan rates to income inequality which further supports our benchmark results.

Additionally, we exclude the two measures of the supply side in the credit market (bank concentration, credit market depth) due to the hypothesised interplay between them and income inequality from our regressions. Results, available upon request, reflect the benchmark results in the case of consumer loan rates, confirming a significant impact of inequality, not only on the overall level of bank loan rates, but also its adverse effect on standard monetary policy transmission. The findings reported for housing loan rates are even more statistically significant in this reduced form, with preserved signs of regression coefficients. The results for small firms loans rates are broadly consistent with our benchmark regression, showing the positive impact of higher income inequality on the level of bank loan rates (i.e., an increase), as well as an impact on the reduction in the IRPT

in the presence of lower inequality. Contrary to the findings in our benchmark regressions presented in section 4.2, the effectiveness of monetary policy transmission in the large firms loans segment is reported to be affected by income inequality in the case of QE policies (resulting in a statistically significant effect also in the case of the shadow rate).

Next, we also test the robustness of our results with regard to the different treatment of our micro data on income distribution, which we use to construct our inequality measures. To be precise, in our benchmark specifications, we trimmed off individuals who had zero or negative equalised disposable incomes from the database. However, in order to test the robustness of our results, we also use two additional treatments of individuals with zero or negative income values and then re-estimate our income inequality measures, subsequently re-running our benchmark regressions on these altered data. First, we replace the negative values with zeros (i.e., windsorising). Second, we trim off the individuals with negative values of income from the database. The results of these robustness tests are available upon request and they broadly correspond to our benchmark findings; in fact, the estimated coefficients retain their robustness and the size of the coefficients remains almost identical. The only exceptions are the coefficient of the interaction term in the case of large firms loans rates and the shadow rate, which turns statistically significant at a 10 % level of significance, albeit very narrowly, and the coefficient of the interaction term in the case of standard monetary policies and small firms loans rates, which loses statistical significance in the second case.

In another robustness check, we test the robustness of our results to the selection of time period of the analysis. Since the first two years covered in our empirical analysis were the years of the global recession, we re-estimate our regressions on only the sample covering the years 2010-2016. This approach enables us to investigate, whether the period of the GFC is driving our baseline results. Furthermore, this robustness check also enables us to investigate the sensitivity of our results to the selection of the time period. The results of this robustness check are broadly qualitatively in line with our baseline results – with the exception of the results for housing loans rates, for which only the result for the effect of inequality on the transmission of QE retains its statistical significance. On the top of that, in the case of large firm loans rates, the coefficients of the interaction terms for Eonia and shadow rate, while retaining their signs, attain statistical

significance. Thus, we conclude that our results do not seem to be driven by the crisis period. For brevity, we do not report the results of these regressions here, but they are available upon request.

Lastly, we investigate the robustness of our results with regards to the selection of the measure of inequality. As a result, in the next robustness check, we use Gini coefficient, as an alternative measure of income inequality. As the Gini coefficient is the most widely used measure of income inequality, we aim to investigate whether our benchmark results hold even when we use the Gini coefficient as an alternative measure of inequality. Nonetheless, we do not expect the results for the Gini coefficient to be completely similar to the results obtained with our benchmark indicators of income inequality – as the Figure A2 in the Appendix clearly demonstrates that our preferred indicators of inequality, which focus rather on the tails of the income distribution, may be better positioned to capture the heterogeneity in income inequality across time and countries, but the main patterns of our findings could still be expected to remain unchanged.

We report the results of the regressions estimated with Gini coefficient as the measure of inequality in Tables A1 and A2 in the Appendix. Using the Gini coefficient as a measure of inequality, we once again find that higher inequality contributes to higher consumer loans rates. Additionally, higher inequality also limits the transmission of standard monetary policy to consumer loans rates. Using the Gini coefficient, we also observe similar finding when using the shadow rate as a broad measure of monetary policy stance. In this case, the coefficient of the interaction term with QE is also statistically significant, but in this regression, the coefficient of the error correction term is insignificant and thus we treat this result with a grain of salt. For housing loans rates, the results obtained when using the Gini coefficient are broadly in line with our benchmark results – though the statistical significance of the coefficients of the interaction terms varies to some extent. For small firm loans rates, using Gini coefficient as a measure of inequality, we also once again find that higher inequality enhances transmission of monetary policies to small firm loans rates – with the exception of CE policies, for which higher Gini coefficient seems to hinder the transmission to small firm loans rates. Finally, for large firm loans rates, our findings obtained for the Gini coefficient are also in line with our benchmark results and we do not find robust evidence that income inequality plays a significant role in influencing the transmission of monetary policy to large

firm loans rates – with the exception of the regression with the shadow rate as a measure of overall monetary policy stance. However, even for the regression with shadow rate, the interaction term is only statistically significant at a 10 % level.

5. Conclusions

In this paper, we have examined the role of income inequality in affecting the transmission of standard and non-standard monetary policies to bank loans rates in the 15 Euro Area member states over the years 2008-2016. We have used the highly disaggregated micro data from the EU-SILC database to create our individual measures of income inequality.

First, we applied the rolling windows approach with the pooled mean group (PMG) estimator. We found that income distribution does have a long-term effect on monetary policy transmission. Furthermore, this approach has enabled us to observe trends, which indicate how the different parts of income distribution affect the transmission of monetary policies. We have found that the lower and upper tails of the income distribution, in particular, play an important part in affecting monetary policy transmission.

Second, using the observed patterns from the rolling windows regressions, we have constructed a single measure of income inequality for each of the monetary policy type and bank loan rate type pairs. This indicator is calculated as a ratio of the share of the population from the lower tail of the distribution to the share of the population from the upper tail of the distribution. According to the results attained using the PMG estimator, higher income inequality reduces the transmission of standard monetary policies to consumer loans rates. We have additionally found that higher inequality reduces the transmission of CE policies to housing loans rates, but we have also found that higher inequality enhances the effects of QE policies on housing loans rates. Furthermore, higher income inequality seems to enhance the transmission of standard, QE and CE policies to small firm loans rates. Nevertheless, we find no evidence that income inequality plays a statistically significant role in affecting the transmission of either standard or non-standard monetary policies to large firm loans rates.

Our results thus indicate that changes in income inequality may not only be treated as a mere side effect of monetary policy, rather, in some cases, persistent income inequality may hinder the transmission of monetary policy. Furthermore, the different income distributions could also contribute to a more significant heterogeneity in the transmission of monetary policies.

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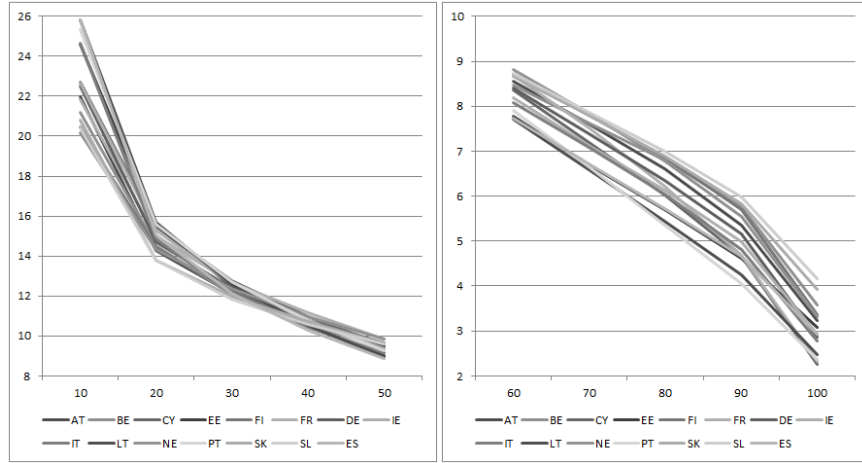
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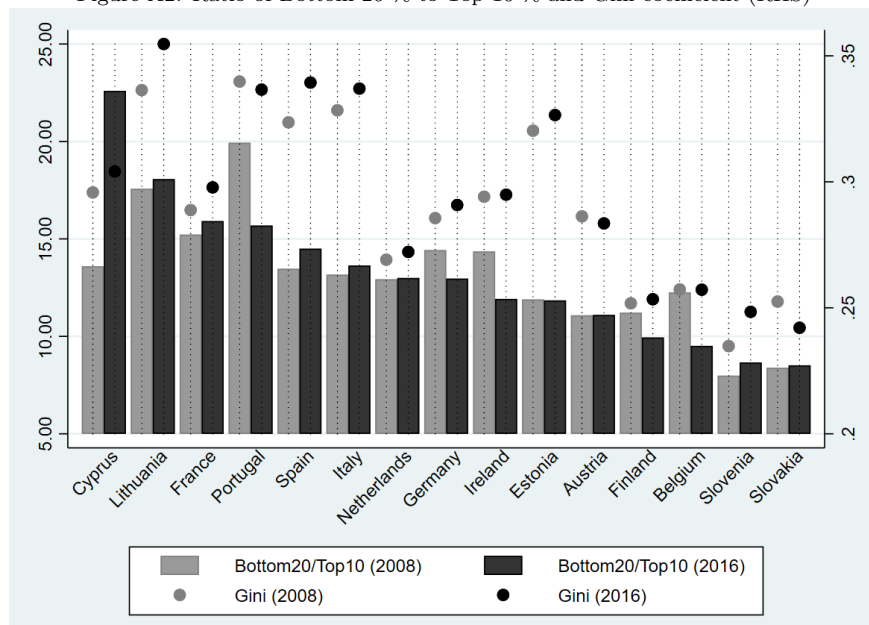
Appendix

Figure A1: Population share of individuals in respective income deciles (average, 2008-2016)



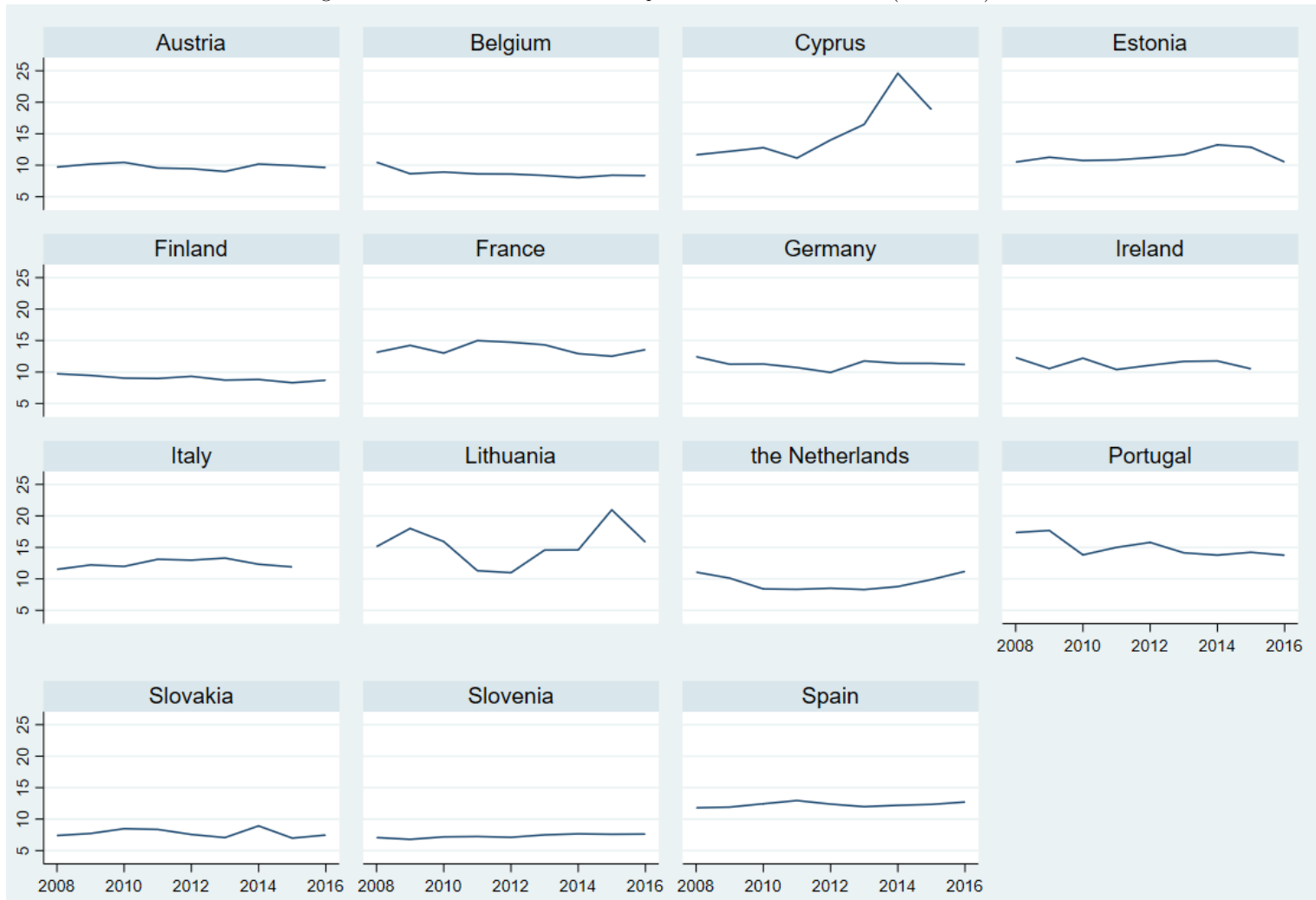
Notes: Figures plot the population share of individuals (y-axis) associated with respective income deciles calculated from the overall income distribution in the EU-SILC database. Data is calculated as an average over the period 2008-2016.

Figure A2: Ratio of Bottom 20 % to Top 10 % and Gini coefficient (RHS)



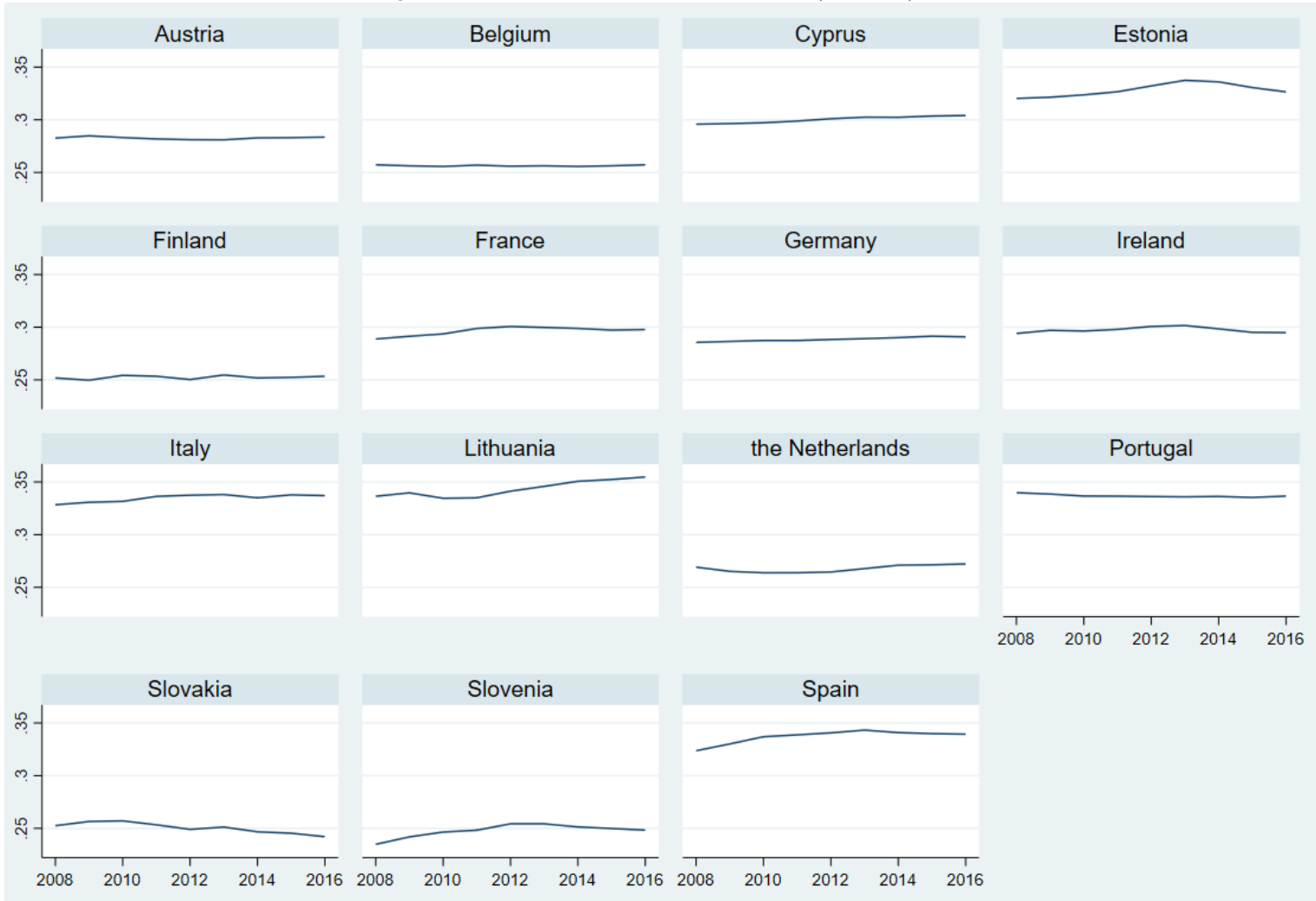
Source: Statistics on Income and Living Condition (EU SILC)

Figure A3: Ratio of Bottom 20 % to Top 10 in Euro Area countries (2008-2016)



Source: Statistics on Income and Living Condition (EU SILC)

Figure A4: Gini coefficient in Euro Area countries (2008-2016)



Source: Statistics on Income and Living Condition (EU SILC)

Figure A5: Bank loans rates in Euro Area countries (2008-2016)

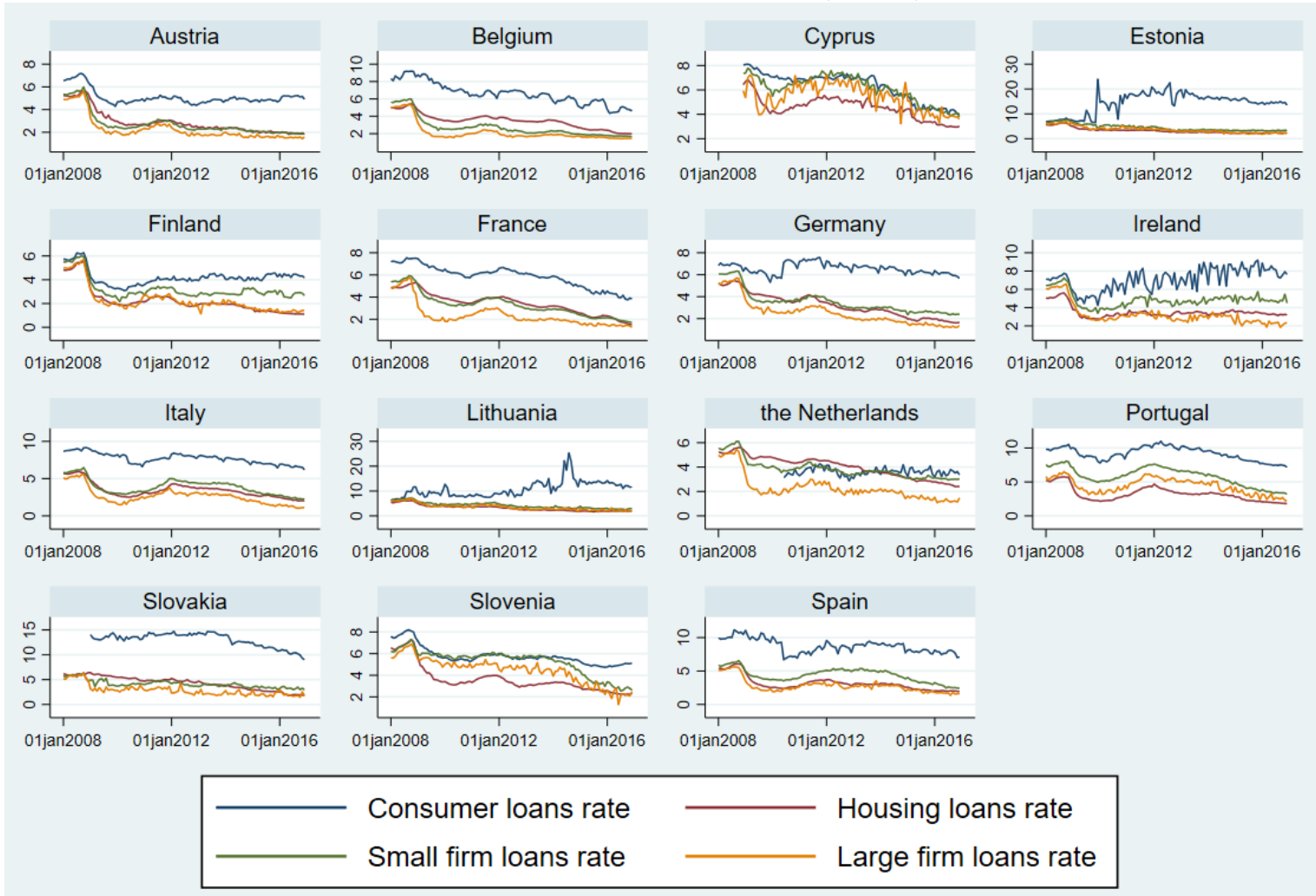
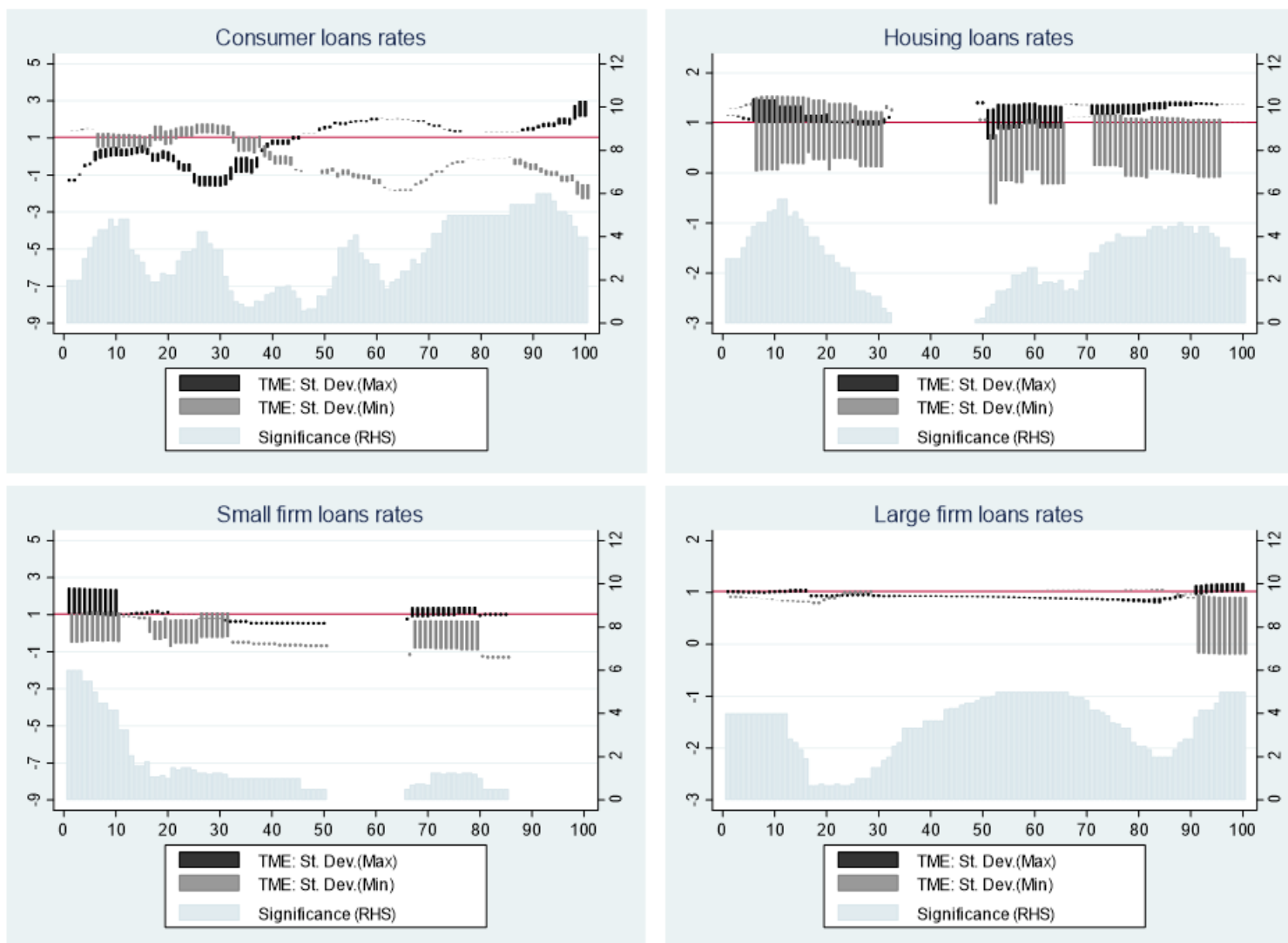


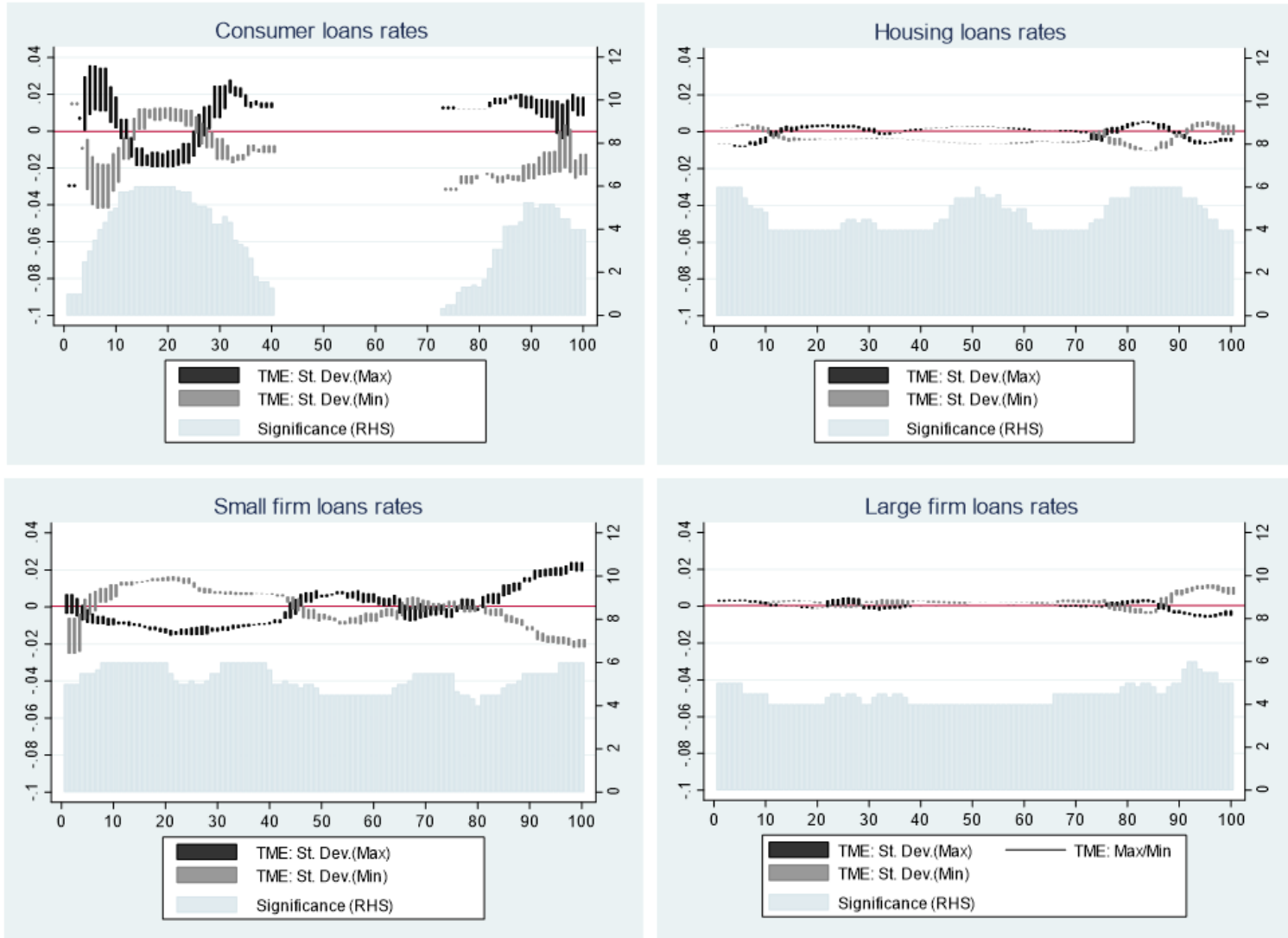
Figure A6: Transmission of standard monetary policies (EONIA) to bank loans interest rates – Total marginal effects (left axis) conditional on income percentiles



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Notes: Total marginal effect (TME) measures conditional response of bank loan rates to one unit change in EONIA evaluated at highest (Max) and lowest (Min) observed levels of income inequality for each percentile of income distribution. Length of the bar indicates standard deviation of individual TME estimates calculated from the rolling windows regressions with several step and windows sizes for defining the income inequality. Only TMEs with statistically significant coefficients are reported. Significance stands for the absolute number of statistically significant TMEs across different rolling windows regressions.

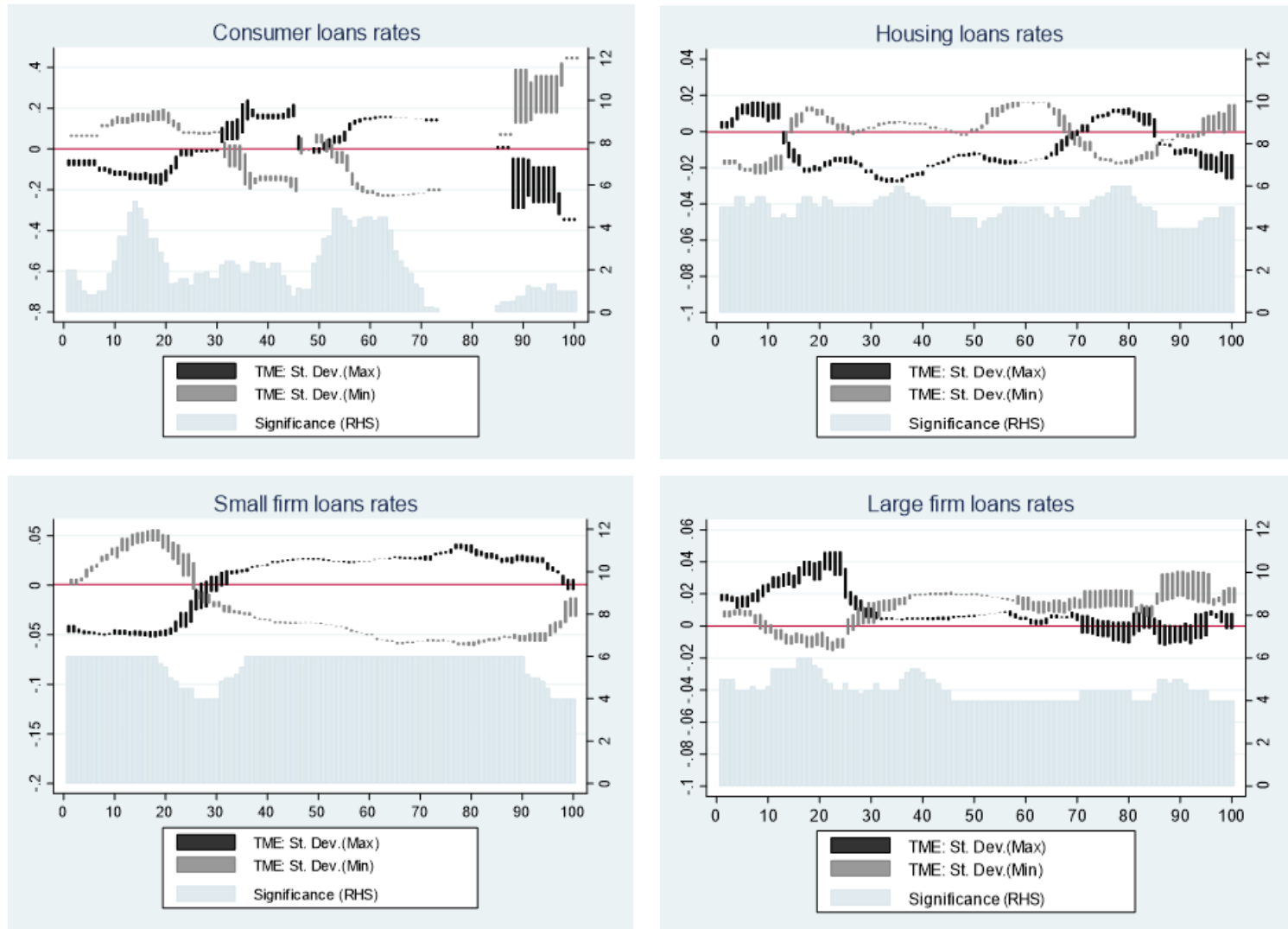
Figure A7: Transmission of credit easing policies (CE) to bank loans interest rates – Total marginal effects conditional on income percentiles



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Notes: Total marginal effect (TME) measures conditional response of bank loan rates to one unit change in measure of CE policy evaluated at highest (Max) and lowest (Min) observed levels of income inequality for each percentile of income distribution. Length of the bar indicates standard deviation of individual TME estimates calculated from the rolling windows regressions with several step and windows sizes for defining the income inequality. Only TMEs with statistically significant coefficients are reported. Significance stands for the absolute number of statistically significant TMEs across different rolling windows regressions.

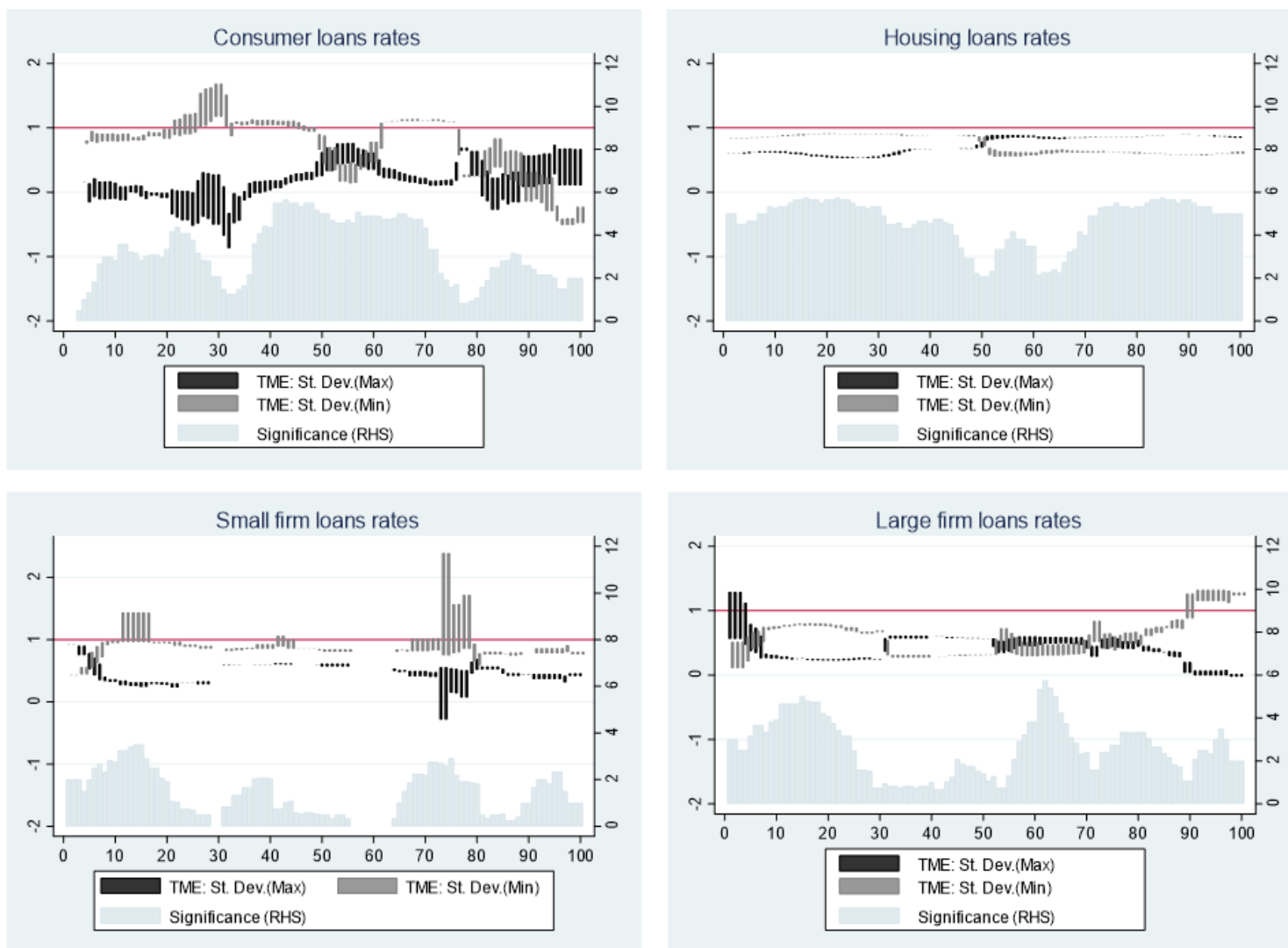
Figure A8: Transmission of quantitative easing policies (QE) to bank loans interest rates – Total marginal effects conditional on income percentiles



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Notes: Total marginal effect (TME) measures conditional response of bank loan rates to one unit change in measure of QE policy evaluated at highest (Max) and lowest (Min) observed levels of income inequality for each percentile of income distribution. Length of the bar indicates standard deviation of individual TME estimates calculated from the rolling windows regressions with several step and windows sizes for defining the income inequality. Only TMEs with statistically significant coefficients are reported. Significance stands for the absolute number of statistically significant TMEs across different rolling windows regressions.

Figure A9: Transmission of expansionary monetary policies (shadow rate) to bank loans interest rates – Total marginal effects conditional on income percentiles



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Notes: Total marginal effect (TME) measures conditional response of bank loan rates to one unit change in shadow rate evaluated at highest (Max) and lowest (Min) observed levels of income inequality for each percentile of income distribution. Length of the bar indicates standard deviation of individual TME estimates calculated from the rolling windows regressions with several step and windows sizes for defining the income inequality. Only TMEs with statistically significant coefficients are reported. Significance stands for the absolute number of statistically significant TMEs across different rolling windows regressions.

Table A1: The effect of Gini coefficient on the transmission of monetary policy to consumer and housing loans rates

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Consumer loans rates					Housing loans rates				
<i>Long-run equation</i>										
EONIA	0.594*** (0.191)	0.580*** (0.224)	1.066*** (0.175)	1.028*** (0.120)		1.264*** (0.063)	1.293*** (0.066)	1.296*** (0.068)	1.200*** (0.053)	
CE			-0.002 (0.002)					-0.003* (0.002)		
QE				0.014*** (0.004)					-0.010*** (0.003)	
Shadow rate					0.110*** (0.028)					0.729*** (0.035)
CDS premium	0.001 (0.001)	0.000 (0.001)	0.006*** (0.002)	0.001*** (0.000)	0.001* (0.001)	0.004*** (0.000)	0.004*** (0.000)	0.005*** (0.001)	0.004*** (0.000)	0.003*** (0.000)
PCA real economy	-0.102 (0.186)	-0.010 (0.139)	0.209** (0.092)	0.428*** (0.101)	0.128** (0.053)	0.341*** (0.056)	0.317*** (0.055)	0.400*** (0.068)	0.345*** (0.051)	0.674*** (0.073)
Bank concentration (%)	0.033* (0.020)	0.001 (0.015)	0.065*** (0.019)	0.011 (0.016)	-0.024*** (0.008)	-0.010*** (0.003)	-0.010*** (0.003)	-0.008* (0.004)	-0.008*** (0.002)	-0.006 (0.004)
Credit to GDP (%)	-0.033*** (0.007)	-0.029*** (0.005)	-0.071*** (0.008)	-0.010*** (0.003)	-0.036*** (0.005)	-0.002 (0.001)	-0.003* (0.001)	-0.000 (0.002)	-0.001 (0.001)	0.000 (0.003)
Gini		0.670*** (0.069)	0.565*** (0.117)	0.423*** (0.096)	0.094*** (0.034)		0.027 (0.019)	-0.011 (0.025)	-0.068** (0.032)	-0.078*** (0.025)
Interact		-0.098* (0.050)	-0.002 (0.003)	-0.007** (0.003)	-0.100*** (0.012)		-0.036*** (0.013)	0.000 (0.000)	0.002** (0.001)	-0.013** (0.007)
Constant	8.055*** (1.145)	9.965*** (1.311)	6.034*** (1.618)	6.082*** (0.804)	9.863*** (0.341)	2.517*** (0.264)	2.593*** (0.249)	2.307*** (0.293)	2.759*** (0.236)	3.352*** (0.334)
<i>Short-run equation</i>										
Error correction	-0.076 (0.059)	-0.102* (0.061)	-0.087 (0.055)	-0.095 (0.063)	-0.076** (0.038)	-0.055*** (0.011)	-0.055*** (0.011)	-0.052*** (0.010)	-0.068*** (0.014)	-0.047*** (0.010)
D.EONIA	-0.791 (0.810)	-0.701 (0.715)	-0.864 (0.771)	-0.783 (0.836)		0.237*** (0.063)	0.248*** (0.068)	0.248*** (0.065)	0.221*** (0.069)	
D.CE			0.000 (0.003)					0.000 (0.000)		
D.QE				0.004 (0.007)					-0.007*** (0.002)	
D.Shadow rate					-0.034 (0.027)					0.000 (0.013)
D.CDS premium	0.006 (0.005)	0.005 (0.004)	0.005 (0.004)	0.005 (0.005)	0.006 (0.005)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
D.PCA real economy	0.118 (0.211)	0.119 (0.209)	0.143 (0.206)	0.112 (0.207)	0.117 (0.213)	0.006 (0.019)	0.007 (0.019)	0.006 (0.019)	0.005 (0.018)	0.008 (0.022)
Observations	1,373	1,373	1,373	1,373	1,373	1,399	1,399	1,399	1,399	1,399

Notes: Interact is defined as the interaction term of the EONIA, CE, QE and the shadow rate and the Gini coefficient. Gini coefficient serves as a measure of income inequality. CE stands for credit easing policies, QE for quantitative easing policies. Standard errors are in parentheses. * indicates significance at the 10% level, ** at the 5% level and *** at the 1% level.

Table A2: The effect of Gini coefficient on the transmission of monetary policy to large firm and small firm loans rates

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Small firm loans rates					Large firm loans rates				
<i>Long-run equation</i>										
EONIA	1.577*** (0.121)	1.197*** (0.072)	1.192*** (0.077)	1.239*** (0.078)		0.913*** (0.018)	0.910*** (0.027)	0.908*** (0.018)	0.921*** (0.015)	
CE			-0.001 (0.002)					0.001** (0.001)		
QE				-0.006 (0.006)					0.012*** (0.001)	
Shadow rate					0.645*** (0.038)					0.570*** (0.035)
CDS premium	0.008*** (0.001)	0.007*** (0.001)	0.005*** (0.001)	0.007*** (0.001)	0.004*** (0.000)	0.003*** (0.000)	-0.000 (0.000)	0.002*** (0.000)	0.001*** (0.000)	0.001* (0.001)
PCA real economy	0.523*** (0.097)	0.414*** (0.078)	0.248*** (0.077)	0.413*** (0.071)	0.619*** (0.078)	0.071*** (0.015)	0.079*** (0.012)	0.075*** (0.015)	0.081*** (0.014)	0.561*** (0.068)
Bank concentration (%)	0.012*** (0.004)	0.030*** (0.003)	0.032*** (0.003)	0.002 (0.003)	0.025*** (0.005)	-0.001 (0.001)	-0.010*** (0.002)	-0.004* (0.002)	-0.004** (0.002)	0.004 (0.006)
Credit to GDP (%)	0.003 (0.002)	0.011*** (0.002)	0.009*** (0.002)	0.012*** (0.002)	0.010*** (0.002)	0.000 (0.001)	0.009*** (0.001)	0.002 (0.001)	0.007*** (0.001)	0.005* (0.003)
Gini		0.016 (0.016)	-0.017 (0.027)	0.120*** (0.034)	0.157*** (0.027)		-0.051*** (0.014)	-0.021 (0.019)	-0.040* (0.023)	0.030 (0.038)
Interact		0.108*** (0.021)	0.002*** (0.001)	-0.003* (0.001)	0.053*** (0.012)		-0.003 (0.009)	0.000 (0.000)	0.001 (0.001)	0.024* (0.013)
Constant	0.727* (0.428)	-1.002*** (0.344)	-0.804** (0.343)	0.942** (0.367)	0.714** (0.363)	1.631*** (0.127)	1.588*** (0.112)	1.676*** (0.128)	1.110*** (0.115)	1.870*** (0.407)
<i>Short-run equation</i>										
Error correction	-0.098** (0.048)	-0.122** (0.053)	-0.110** (0.045)	-0.112* (0.062)	-0.063*** (0.009)	-0.250*** (0.051)	-0.196*** (0.050)	-0.232*** (0.050)	-0.263*** (0.062)	-0.102*** (0.014)
D.EONIA	0.038 (0.309)	0.077 (0.258)	0.135 (0.191)	0.092 (0.260)		0.190 (0.134)	0.599* (0.320)	0.409*** (0.143)	0.345* (0.188)	
D.CE			0.000 (0.001)					0.003** (0.001)		
D.QE				-0.001 (0.004)					-0.025** (0.013)	
D.Shadow rate					0.011 (0.021)					-0.043 (0.045)
D.CDS premium	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	0.000 (0.001)	0.000 (0.001)	0.002 (0.002)	0.001 (0.001)	0.001 (0.001)	0.001 (0.002)
D.PCA real economy	0.027 (0.034)	0.019 (0.038)	0.013 (0.044)	0.021 (0.032)	-0.010 (0.047)	0.134** (0.066)	0.106* (0.055)	0.119** (0.061)	0.124* (0.065)	0.112* (0.058)
Observations	1,399	1,399	1,399	1,399	1,399	1,399	1,399	1,399	1,399	1,399

Notes: Interact is defined as the interaction term of the EONIA, CE, QE and the Gini coefficient. Gini coefficient serves as a measure of income inequality. CE stands for credit easing policies, QE for quantitative easing policies. Standard errors are in parentheses. * indicates significance at the 10% level, ** at the 5% level and *** at the 1% level.

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Univerzita Karlova v Praze, Fakulta sociálních věd
Institut ekonomických studií [UK FSV – IES] Praha 1, Opletalova 26
E-mail : ies@fsv.cuni.cz <http://ies.fsv.cuni.cz>